Cancer Biology

Deuterium Metabolic Imaging Phenotypes Mouse Glioblastoma Heterogeneity Through Glucose Turnover Kinetics

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Rui V Simões, **Rafael N Henriques, Jonas L Olesen, Beatriz M Cardoso, Francisca F Fernandes, Mariana AV Monteiro, Sune N Jespersen, Tânia Carvalho, Noam Shemesh**

Preclinical MRI, Champalimaud Research, Champalimaud Foundation, Lisbon, Portugal • Neuroengineering and Computational Neuroscience, Institute for Research and Innovation in Health (i3S), Porto, Portugal • Center of Functionally Integrative Neuroscience (CFIN) and MINDLab, Department of Clinical Medicine, Aarhus University, Aarhus, Denmark; Department of Physics and Astronomy, Aarhus University, Aarhus, Denmark • Histopathology Platform, Champalimaud Research, Champalimaud Foundation, Lisbon, Portugal

Abstract

Glioblastomas are aggressive brain tumors with dismal prognosis. One of the main bottlenecks for developing more effective therapies for glioblastoma stems from their histologic and molecular heterogeneity, leading to distinct tumor microenvironments and disease phenotypes. Effectively characterizing these features would improve the clinical management of glioblastoma. Glucose flux rates through glycolysis and mitochondrial oxidation have been recently shown to quantitatively depict glioblastoma proliferation in mouse models (GL261 and CT2A tumors, 38±3 mm^3) using dynamic glucose-enhanced (DGE) deuterium spectroscopy. However, the spatial features of tumor microenvironment phenotypes remain hitherto unresolved. Here, we develop a DGE Deuterium Metabolic Imaging (DMI) approach for profiling tumor microenvironments through glucose conversion kinetics. Using a multimodal combination of tumor mouse models, novel strategies for spectroscopic imaging and noise attenuation, and histopathological correlations, we show that tumor lactate turnover mirrors phenotype differences between GL261 and CT2A mouse glioblastoma (59±7 mm^3), whereas peritumoral glutamate-glutamine recycling is a potential marker of invasion capacity in pooled cohorts, linked to secondary brain lesions. Our findings were validated by histopathological characterization of each tumor, including cell density and proliferation, peritumoral infiltration, and distant migration. Our study bodes well for precision neuro-oncology, highlighting the importance of mapping glucose flux rates to better understand the metabolic heterogeneity of glioblastoma and its links to disease phenotypes.

eLife assessment

This work describes a **convincingly** validated non-invasive tool for in vivo metabolic phenotyping of aggressive brain tumors in mice brains. The analysis provides a **valuable** technique that tackles the unmet need for patient stratification and hence for early assessment of therapeutic efficacy. However, wider clinical applicability of the findings can be attained by expanding the work to include more diverse tumor models.

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Introduction

Glioblastoma (glioma grade 4 or GBM) are the most aggressive primary brain tumors in adults. The dismal prognosis of such heterogeneous tumors is mostly attributed to recurrence, associated with limited response to treatment and an infiltrative pattern that prevents full surgical resection [1]. Glioblastoma heterogeneity is reflected in the tumor microenvironment, where glioma cells constantly adapt to their evolving microhabitats, with different biophysical characteristics, progression stages, and therapy resistance [2]. To sustain active proliferation, cancer cells exchange metabolic intermediates with their microenvironment [3] and undergo metabolic reprogramming [4], relying heavily on aerobic glycolysis – upregulation of glucose uptake concomitant with lactate synthesis, leading to acidification of the tumor microenvironment. While this so-called Warburg effect [5] favors e.g. invasion [6], metabolic plasticity [7, 8] is becoming increasingly associated with malignant phenotypes [9]. Namely, mitochondrial oxidation (e.g. glucose metabolism through the tricarboxylic acid cycle, TCA) is linked with microenvironment adaptation and tumor progression [10].

The ability to use both glycolysis and mitochondrial oxidation pathways is a critical feature of GBM, which has been demonstrated from preclinical models to patients [11–13]. More recently, specific dependencies/proclivities towards those metabolic pathways are beginning to reveal GBM subtypes with prognostic value in human cell lines and patient-derived cells [14–16]. Importantly, the latest WHO classification of central nervous system tumors now distinguishes two metabolic phenotypes of adult GBM based on molecular assessment of a specific TCA cycle mutation (isocitrate dehydrogenase, IDH), namely into grade 2-4 gliomas (IDH-mut) and grade 4 GBM (IDH-wt) [17]. The prognostic value of GBM metabolic phenotypes clearly calls for non-invasive imaging methodologies capable of resolving the different subtypes, both for diagnosis and for treatment response monitoring. However, such methods are scarce.

Deuterium metabolic imaging (DMI) has been proposed for mapping active metabolism *de novo* in several tumor models [18–24]. While this has also been demonstrated in GBM patients [18], and more recently in mouse models of patient-derived GBM subtypes [25], mapping glucose metabolic fluxes remains unaddressed in these tumors due to the poor temporal resolution of DMI; particularly for glucose mitochondrial oxidation. Leveraging the benefits and risks of denoising methods for MR spectroscopy [26–28], we recently combined Deuterium Magnetic Resonance Spectroscopy (^{2}H-MRS) [29] with Marcheku-Pastur PCA (MPPCA) denoising [30] to propose Dynamic Glucose-Enhanced (DGE) ^{2}H-MRS [31], demonstrating its ability to quantify glucose fluxes through glycolysis and mitochondrial oxidation pathways *in vivo* in mouse GBM, which in turn revealed their proliferation status.

Here, we develop and apply a novel rapid DGE-DMI method to spatially resolve glucose metabolic flux rates in mouse GBM and reach a temporal resolution compatible with its kinetic modeling. For this, we adapt two advances of PCA denoising – tensor MPPCA [32, 33] and threshold PCA denoising [34] – and apply it for regional metabolic assessment of mouse GBM. First, we validated our novel approach *in vivo* for its ability to map glucose fluxes through glycolysis and mitochondrial oxidation in mouse GBM. Then, we investigate the potential of our new approach for depicting histopathologic differences in two mouse models of glioblastoma, including cell proliferation, peritumoral infiltration and migration. For this we used the same allograft mouse models of GBM, induced with CT2A and GL261 cell lines [35–39], but at more advanced stages of progression [31].

Results

MRI assessment of mouse GBM

Multi-parametric MRI provided a detailed characterization of each cohort at endpoint. Volumetric T2-weighted MRI indicated consistent tumor sizes across CT2A and GL261 cohorts (58.5±7.2 mm^3). GL261 tumors were studied sooner after induction (17±0 vs 30±5 days post- injection, p=0.032), explaining the lower animal weights in this cohort (22.4±0.6 vs 25.7±0.9 g, p=0.017). DCE T1-weighted MRI indicated higher vascular permeability (0.85±0.11 vs 0.43±0.05 10^{-2}/min, p=0.012) and a tendency for larger extracellular volume fractions (0.26±0.03 vs 0.18±0.02, p=0.056) in the GL261 tumors compared to CT2A. However, DCE T1-weighted MRI was carried out only in 80% of the mice due to time restrictions. This information is detailed in Table S1, where quantitative assessment of DGE-DMI, DCE-T1 and histologic parameters is displayed for tumor and tumor border regions, based on ROI analysis.

DGE-DMI in mouse GBM

Tumor metabolic assessment was performed with DGE-DMI in CT2A vs GL261 cohorts. No differences in RF coil quality or magnetic field homogeneity were detectable between the two cohorts: Q-factor ^{2}H, 175±8 vs 176±9 (p=0.8996), respectively; FWHM ^{1}H (VOI), 29.2±6.6 vs 26.0±4.3 Hz (p=0.3837), respectively. DGE-DMI was used to map the natural abundance semi- heavy water signal (DHO) as well as the dynamic conversion of deuterium-labelled glucose (Glc) to its downstream products, lactate (Lac) and glutamate-glutamine (Glx) pools, in tumor and peritumor brain regions (**Fig. 1A**). Tensor PCA denoising improved the spectral quality compared to the original data, without any depictable effects in the relative spatial distributions of SNR (Fig. S1), leading to a consistent and significant ~3-fold SNR increase across all the subjects (from 6.4±0.1 before denoising to 20.1±0.4 after denoising, Table S1).

Spectral quantification of DGE-DMI data in each voxel and time point rendered time-course *de novo* concentration maps for each metabolite (DHO, Glc, Glx, and Lac), in both GBM cohorts (**Fig 1B**). Voxel-wise averaging of DGE-DMI time-course data after Glc injection generated average metabolic concentration maps for each tumor (**Fig. 1C**). Thus, Lac concentration was visually higher in the tumor regions, due to enhanced glycolysis; whereas Glx was more apparent in the adjacent non/peri-tumoral areas, consistent with a more prevalent oxidative metabolism in the normal brain. Kinetic fitting of DGE-DMI time-course concentration maps rendered glucose flux maps, namely its maximum consumption rate (V_{max}) and flux rates through glycolysis (V_{lac} and k_{lac}) and mitochondrial oxidation (V_{glx} and k_{glx}) (**Fig 1D**). Both cohorts displayed higher glycolytic metabolism in the tumors and more pronounced glucose oxidation in non-tumor regions, aligned with average concentration maps.

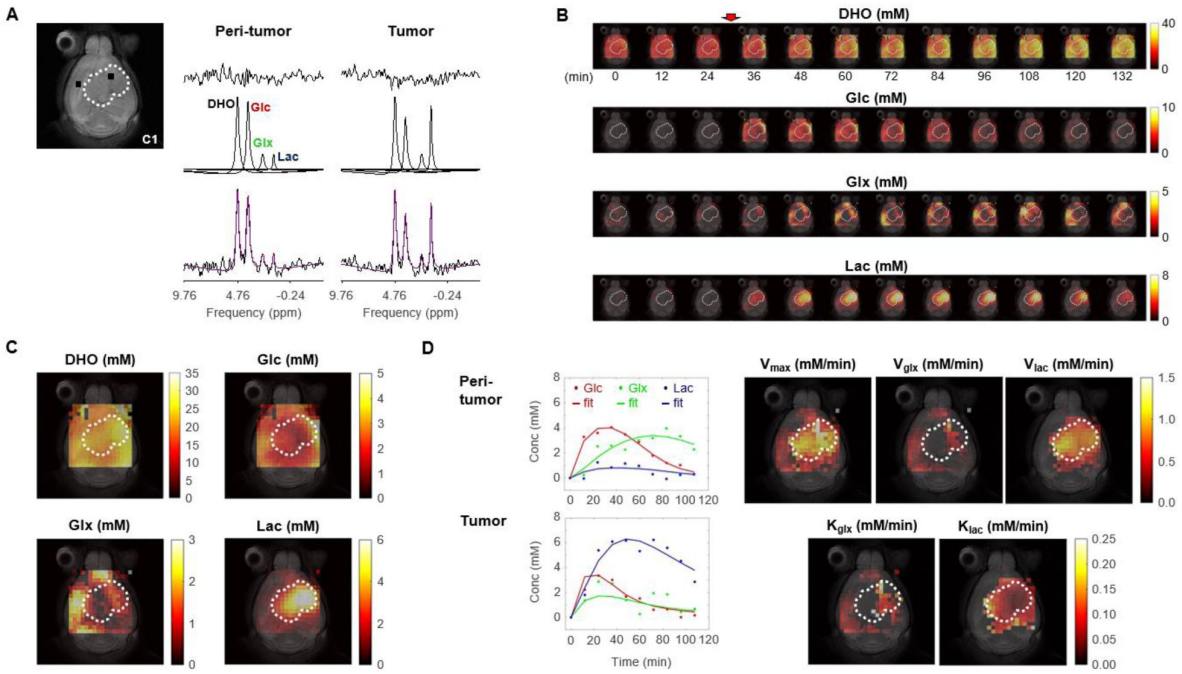


Fig. 1.

Metabolic concentration and flux maps from DGE-DMI in mouse GBM.

Example of a CT2A tumor (C1). **A** T2-weighted reference image (top-left) displaying the tumor region (dashed lines) and representative peri-tumor and tumor voxels (back dots), and respective spectral quantifications (right-side): bottom, raw spectrum (black) with overlaid estimation (purple); center, individual components for each metabolite peak (black - semi-heavy water, DHO (black); deuterated glucose, Glc (red); and glucose-derived glutamate-glutamine and lactate, Glx (green) and Lac (blue)); top, residual. **B** Time-course *de novo* concentration maps for each metabolite (mM) following Glc i.v. injection (red arrow). **C** Average concentration maps for each metabolite after Glc injection. **D** Time-course concentration plots for each metabolite (dots) and respective kinetic fitting (straight lines), displayed for the peri-tumor and tumor voxels shown in A (same color codes) and applied to all the voxels to generate glucose flux maps: maximum consumption rate (V_{max}); and respective individual rates for lactate synthesis (V_{lac}) and elimination (k_{lac}), and glutamate-glutamine synthesis (V_{glx}) and elimination (k_{glx}).

Histopathology assessment of GBM cohort differences

Histopathological analysis consisted of screening the CT2A and GL261 brain tumors for morphological features, including qualitative assessment of cell density, hemorrhage, tumor vessels, necrosis, quantification of peripheral infiltration and quantification of tumor proliferation index, while blinded to the in vivo MRI/MRS data – Table S2. Thus, tumors were scored individually for the following stromal-vascular phenotype, as in [31], where: pattern I corresponds to predominance of small vessels, complete endothelial cell lining and sparse hemorrhages; pattern II to vasodilation and marked multifocal hemorrhages; pattern III to predominance of necrosis of the vascular wall, incomplete endothelial cell lining, vascular leakage, and edematous stroma; and pattern IV to tumors with absence of clear vascular spaces and edematous stroma.

Stromal-vascular phenotypes reflected the more advanced stages of tumor progression in which these tumors were collected, as compared to our previous study [31]. Particularly, CT2A (n=5) presented patterns I to III, whereas all GL261 (n=5) matched pattern IV. Moreover, the increased infiltrative and migratory characteristics of GL261 compared to CT2A tumors were evident in their irregular tumor borders and higher incidence of secondary brain lesions (**Fig 2A**). These findings collectively suggest a more invasive and aggressive pattern of GL261 tumors, characterized by reduced cell-cell adhesion and enhanced migratory potential compared to CT2A. This difference between the two groups was further highlighted in the quantitative regional analysis, in which Tumor-to-Border ROI ratios exhibited 47% lower cell density (p=0.004) and 32% higher cell proliferation (p=0.026) in GL261 compared to CT2A (**Fig 2B**).

Despite the more advanced stages of tumor progression, the results were largely consistent with the marked morphological differences between the two models [31]: CT2A with dense, cohesive and homogeneous cell populations (**Fig 2A**, left-side); GL261 displaying marked heterogeneity, with poorly cohesive areas and more infiltrative growth (**Fig 2A**, right-side). Quantitative assessment (nuclear counts) further confirmed a nearly 2-fold lower cell density of GL261 tumors compared to CT2A (4.9 vs 8.2 $\cdot 10^3$ cells/μm^2, p<0.001) despite their similar proliferation index (Table S1); and tumor cell density correlated with cell proliferation, strongly for CT2A (R=0.96, p=0.009) and the same tendency detected for GL261 (R=0.74, p=0.151).

Tumor volume and whole-brain gross assessment of cell density, cell proliferation, and glucose metabolism also revealed strong inter-subject correlations in both cohorts (Fig. S2): *de novo* glutamate-glutamine accumulation decreased with tumor size ($R_{CT2A/\ GL261/\ pooled}$: -0.597/ - 0.753/ -0.455), consistent with its role as marker of oxidative metabolism in the normal brain; lactate synthesis rate increased with cellularity ($R_{CT2A/\ GL261/\ pooled}$: +0.921/ +0.685/ +0.852), also aligned with enhanced glycolysis in growing tumors; whereas glucose accumulation reflected cell proliferation ($R_{CT2A/\ GL261/\ pooled}$: +0.469/ +0.528/ +0.440).

Regional assessment of glucose metabolism in the tumor microenvironment

Initial intra-tumor analysis of DGE-DMI and DCE-T1 maps (pixel-wise correlations in tumor ROIs) indicate stronger correlations between *de novo* lactate accumulation (Lac) and vascular permeability (k^{trans}) in both cohorts (R between [+0.306 +0.741]), and extracellular space (v_e) to some extent (R between [-0.084 +0.804]) – both less apparent without tensor PCA denoising (R between [+0.089 +0.647] and [-0.160 +0.684], respectively) (Fig. S3). Such accumulation of lactate according to local vascular permeability mostly reflected regional differences in glycolytic fluxes (V_{lac}: R between [-0.066 +0.510]), rather than lactate elimination rates (k_{lac}: R between [- 0.643 +0.460]). No additional correlations were detected.

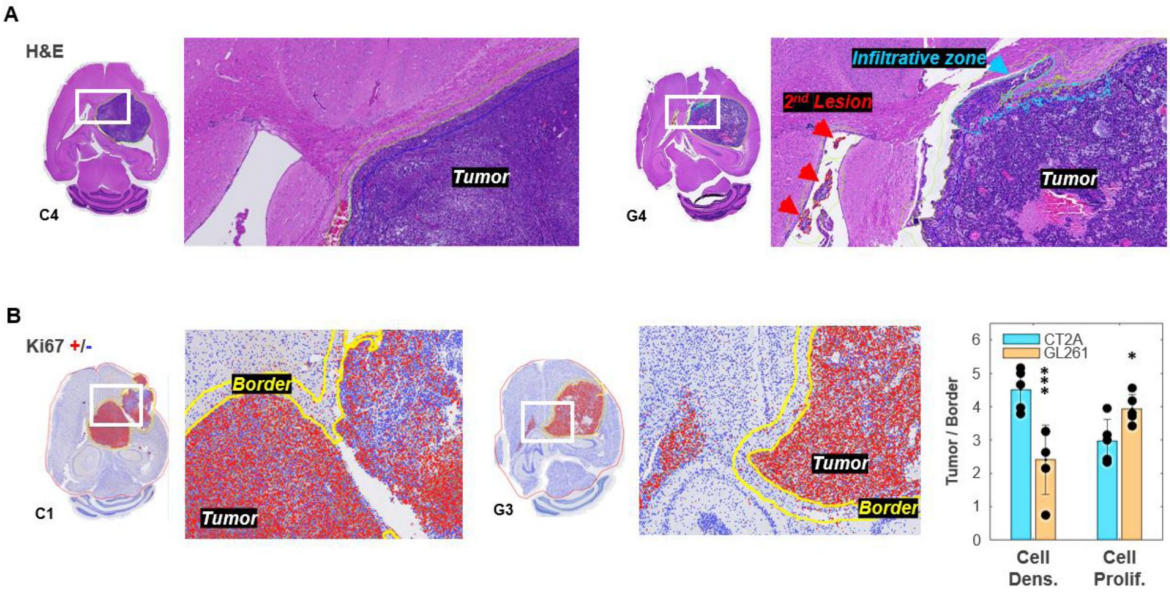


Figure 2

Histopathologic and immunohistochemical assessment in two mouse models of GBM.

A H&E-stained sections with high magnification to highlight annotations of tumor, infiltrative zones in the tumor rim (blue), and secondary lesion (red), in CT2A and GL261 tumors (subjects C4 and G4, respectively). **B** Ki67 immuno-stained sections with overlaid detection of positive (red) and negative (blue) cells; and high magnification to highlight annotations of tumor and tumor border (yellow lines), in CT2A and GL261 tumors (subjects C1 and G3, respectively); and GBM cohort differences in tumor/border ratios of cell density and cell proliferation (dots representative of average values for each subject). CT2A (n=5) vs GL261 (n=5): * p<0.05; *** p<0.001; unpaired *t*-test. Error bars: standard deviation.

GL261 tumors accumulated significantly less lactate in the core (1.60±0.25 vs 2.91±0.33 mM: -45%, p=0.013) and border regions (0.94±0.09 vs 1.46±0.17 mM: -36%, p=0.025) than CT2A – **Fig 3 A-B**, Table S1. Lower tumor lactate levels were associated with higher lactate elimination rate, k_{lac} (0.11±0.1 vs 0.06±0.01 mM/min: +94%, p=0.006) – **Fig 3B**. Further analysis of tumor/border metabolic ratios (Table S3) revealed +38% glucose (p=0.002) and -17% lactate (p=0.038) concentrations, and +55% higher lactate consumption rate (p=0.040) in the GL261 cohort. Moreover, lactate elimination rate correlated inversely with "tumor age" (time post- induction) in pooled cohorts (R=-0.66, p=0.039), and more consistently with tumor vascular permeability (k^{trans}: R=0.78, p=0.022) (**Fig 3 C**), rather than washout rate (k_{ep}: R=0.61, p=0.109).

Association between glucose metabolism and peritumoral invasion and migration

Finally, we investigated the association between glucose metabolism and phenotypic features of tumor aggressiveness, namely cell proliferation and tumor cell invasion and migration associated with secondary brain lesions. Only the more infiltrative GL261 cohort displayed inter-subject associations between tumor cell proliferation ($Ki67^+$ %) and metabolism, namely inverse correlations with tumor border/peritumoral glucose oxidation rate (V_{glx}: R=-0.91, p=0.030) and glucose-derived glutamate-glutamine elimination rate (k_{glx}: R=-0.99, p<0.001). Regrouping subjects according to glioma cell invasion and migration concomitant with secondary brain lesions (presence: C1, G3, G4, G5; vs. absence: C2, C3, C4, C5, G1, G2) revealed lower *de novo* glutamate-glutamine levels in peritumor brain regions (Glx: -37%, p=0.013), which were associated with its higher elimination rate (k_{glx}: +69%, p=0.012) – **Fig 4**.

Discussion

Glioblastomas are aggressive brain tumors with a poor prognosis, largely due to their inter- and intra-tumor heterogeneity and lack of non-invasive methods to assess it. Here we developed and applied a DGE-DMI approach capable of generating metabolic concentration maps and flux rates in two mouse models of glioblastoma, based on unambiguous spectral quantification according to quality criteria. Our results suggest that glycolytic lactate turnover mirrors phenotype differences between the two glioblastoma models, whereas glucose-derived glutamate-glutamine recycling could underly glioma cell migration leading to secondary lesions. This information became more readily available when using the tensor PCA method for spectral denoising.

Tensor PCA denoising increased spectral SNR by ~3-fold, consistently improving spectral quality observed in tumor and peritumoral regions without altering the spatiotemporal profiles of the metabolic concentration maps (Fig S4). While this had no apparent effect on metabolic concentration maps (Figs S5-6), it significantly improved the kinetic modeling performance (Fig S7) and rendered better quality metabolic flux maps in CT2A and GL261 cohorts. Thus, 63% increased pixel detectability enabled capturing more spatial features in the latter without affecting parameter estimates or introducing group differences (Figs S8-9).

Gross whole brain analysis revealed strong inter-subject correlations in both cohorts, such as higher lactate synthesis rate with increasing cellularity – consistent with enhanced glycolysis in growing tumors – whereas intra-tumor pixel-wise analysis suggested lactate accumulation according to local vascular permeability, mostly associated with regional differences in glycolytic fluxes. Such pixel-wise analyses might be misleading since *de novo* lactate diffuses quickly within tumor extracellular spaces and peritumoral regions [40], with spatiotemporal dynamics not fully captured by DGE-DMI. Namely, water diffusion in GL261 tumors *in vivo* (apparent diffusion

Figure 3

Mouse GBM models with different histopathologic phenotypes underlied by regional differences in lactate metabolism.

A Metabolic maps of *de novo* lactate accumulation (mM) and respective consumption/elimination rates (mM/min), in tumor and tumor border regions (delineated by dashed lines) of CT2A and GL261 tumors (subjects C1 and G3, respectively). **B** GBM cohort differences in *de novo* lactate accumulation (Lac) and consumption/elimination rates (k_{lac}). **C** Strong linear correlations (indicated by the Person correlation coefficient, R) of lactate consumption/elimination rates with (top) time post-tumor inoculation in each cohort, and (bottom) tumor vascular permeability in pooled cohorts. CT2A (n=5) vs GL261 (n=5): * p<0.05; ** p<0.01; unpaired *t*-test. Tumor (n=5, each cohort) vs Border (n=5, each cohort): # p<0.05; ## p<0.01; paired *t*-test. Error bars: standard deviation. Bar plot dots representative of average pixel values for each subject.

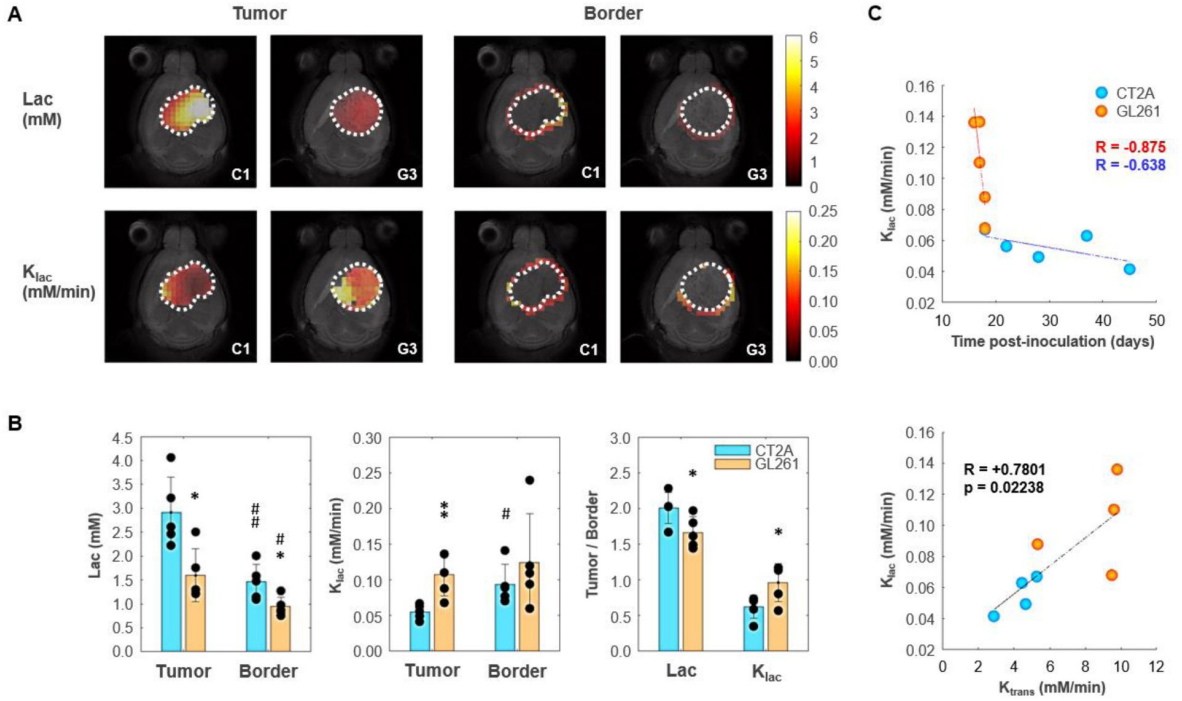
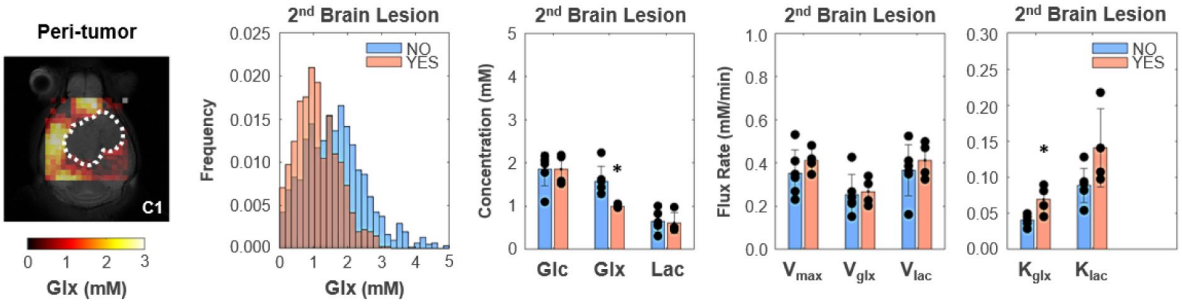


Figure 4

Peritumoral metabolic changes consistent with glutamate-glutamine recycling mirror GBM infiltration and migration leading to secondary brain lesions.

Metabolic map (**left-side:** C1 tumor), histogram distributions (**center**), and bar plot comparison of mean values (**right-side:**), showing significant decreases in peritumoral glutamate-glutamine accumulation (Glx) and increases in its consumption/elimination (k_{glx}) in pooled GL261 and CT2A cohorts displaying secondary brain lesions (n=4; vs n=6 without): * p<0.05; unpaired *t*-test. Error bars: standard deviation. Bar plot dots representative of average pixel values for each subject.



coefficient ~10^{-3} mm^2/s [41, 42]) extends beyond the in-plane voxel area (0.56×0.56 = 0.31 mm^2) during each time frame (12 min). Thus, we focused instead on inter-tumor ROI analysis of glucose metabolic fluxes, in tumor and peritumoral (border) regions.

Compared to our previous study using the same GBM models [31], larger tumors (59±7 vs 38±3 mm^3) display more disrupted stromal-vascular phenotypes (H&E scores: CT2A I-III vs I; GL261, IV vs I-IV) and weaker cell-cell interactions (lower cohesiveness) (Table S2), associated with lower vascular permeability (k^{trans}: 6±1 vs 14±1 10^3/min) and leading to lower glucose oxidation rates (V_{glx}: 0.28±0.06 vs. 0.40±0.08 mM/min), but remarkably similar glycolytic fluxes (V_{lac}: 0.59±0.04 vs. 0.55±0.07 mM/min). Thus, glycolysis flux rates are relatively well preserved across GL261 and CT2A mouse GBM models, regardless of tumor volume and vascular permeability.

GL261 tumors were examined earlier after induction than CT2A (17±0 vs. 30±5 days, p = 0.032), displaying similar volumes (57±6 vs. 60±14, p = 0.813) but better vascular permeability (8.5±1.1 vs 4.3±0.5 10^3/min: +98%, p=0.001), lower cell density (4.9±0.2 vs. 8.2±0.3 10^{-3} cells/μm^2: -40%, p<0.001), and more disrupted stromal-vascular phenotypes and infiltrative growth (5/5 vs 0/5). Such GBM cohort differences were markedly reflected in their regional lactate metabolism. Thus, GL261 tumors accumulated roughly -40% less lactate in tumor and tumor border regions, associated with +94% higher lactate elimination rate rather than glycolytic rate differences in tumor regions, as could be assumed solely based on metabolic concentration maps.

Tumor core vs tumor border analyses further suggest that lactate metabolism reflects regional histologic differences between the two cohorts: lactate accumulation mirrors cell density gradients, whereas lactate consumption/elimination rate coarsely reflects differences in cell proliferation. This is consistent with GL261's lower cell density and cohesiveness, more disrupted stromal-vascular phenotypes, and infiltrative growth pattern at the tumor border area, where relatively lower cell division is expected [43]. Altogether, our results suggest increased lactate consumption rate (active recycling) in GL261 tumors with higher vascular permeability, e.g. as a metabolic substrate for oxidative metabolism [44] promoting GBM cell survival and invasion [45]. While, lactate shuttling within the tumor microenvironment is also reported in other tumor types, between cancer cells [46] and between cancer and stromal cells [47, 48], it should be noted that oxidative phosphorylation inefficiency has been extensively documented in cancer cells, including GBM [49], largely associated with hypoxic niches and in agreement with our measurements of lower glucose oxidation rate (V_{glx}) in tumor vs. peritumoral regions.

The lower glucose oxidation rates measured in this study compared with smaller, better perfused tumor [31], are in good agreement with our previous data indicating quick adaptation of this pathway flux according to oxygen availability in the tumor microenvironment [31]. Under such physiological conditions – underlying more advanced progression stages, reflected in more disrupted stromal-vascular phenotypes – tumor glucose oxidation rate was not associated with cell proliferation index, consistent with previous observations [31]. Instead, tumor cell proliferation was inversely correlated with tumor border/peritumoral glucose oxidation rate and glucose-derived glutamate-glutamine elimination rate in more infiltrative GL261 tumors; but not in CT2A. This observation is consistent to some extent with GL261 cells' and tumor's ability to modulate mitochondrial metabolism according to their microenvironment (e.g. oxygen availability [31]), which is likely to occur during their progression from more circumscribed/local cell proliferation towards more disrupted stromal-vascular phenotypes with higher peritumoral infiltration and distant migration.

Notably, glucose-derived glutamate-glutamine displayed -37% lower levels and +69% higher elimination rate in peritumor regions of mouse brains bearing secondary GBM lesions (respective primary tumors displaying +146% increased glucose oxidation rate, detectable only with tensor PCA denoising – Fig S10). This could be associated with glutamate-glutamine-driven mitochondrial metabolism, through the TCA cycle coupled with oxidative phosphorylation (more prevalent in the

normal brain) and/or via substrate level phosphorylation for ATP synthesis – glutaminolysis (as reported in glioma cells, e.g. CT2A [50]). While patient-derived xenograft models would be more suited to recapitulate human GBM infiltration, our observations are well aligned with the pivotal role of mitochondrial metabolism in cancer cells with higher motile potential, as reported in human GBM [51] and in mouse and human breast cancer cell lines [52, 53]. Particularly, the dynamics of glutamate shuttling underlying neuronal-glioma cell communication and promoting GBM infiltration, are increasingly reported by the emerging field of cancer neuroscience [54]. Therefore, our results suggest that glucose mitochondrial metabolism mirrors GBM progression in mouse GL261 and CT2A models: more prevalent in smaller, well perfused tumors, where glucose oxidation rate correlates with tumor cell proliferation [31]; lower in larger, more poorly perfused tumors, where glutamate-glutamine recycling may reflect a phenotype associated with secondary brain lesions.

Despite the excellent performance of tensor PCA denoising – 3-fold increase in SNR, approaching the original/raw values obtained previously with single-voxel ^{2}H-MRS data (SNR~20, [31]) – no further improvements in SNR could be achieved by FID averaging within the tumor ROI (Fig S11). Therefore, further DGE-DMI preclinical studies aimed at detecting and quantifying relatively weak signals, such as tumor glutamate-glutamine, should improve basal SNR with higher magnetic field strengths, more sensitive RF coils, and advanced DMI pulse sequences [55]). In the kinetic model, the extracellular volume fraction was fixed to ensure model stability, as previously demonstrated using the tumor average across all subjects [31]. This approximation may not fully reflect the intra- and inter-tumor heterogeneity of this parameter in both cohorts, and may not be representative of its peritumoral regions. Still, we opted for this approach, rather than pixel-wise adjustments according to DGE-T1 extracellular volume fraction maps, given (i) the relative insensitivity of the model to the actual extracellular volume fraction value used [31], also verified in the present study (Fig S12); and particularly, because (ii) we did not have DCE-T1 data for the full cohort, thus it was not feasible to perform individual corrections, which in any case would ultimately be prone to error at tumor periphery/border regions, where exact delimitations are typically debatable.

In summary, DGE-DMI quantitatively maps glycolysis and mitochondrial oxidation fluxes in mouse GBM, highlighting its importance for metabolic characterization and potential for *in vivo* GBM phenotyping. In large tumors, lactate metabolism underlies mouse GBM model-specific features, consistent with faster turnover in more disrupted stromal-vascular phenotypes and mirroring intra-tumor gradients of cell density and proliferation, whereas glutamate-glutamine recycling may reflect a phenotype associated with secondary brain lesions. Tensor PCA denoising significantly improved spectral signal-to-noise, which helped reveal such associations between regional glucose metabolism and phenotypic features of intra- and inter-tumor heterogeneity. These results clearly highlight the importance of mapping pathway fluxes alongside *de novo* concentrations to improve the characterization of the complex and dynamic heterogeneity of GBM metabolism. This may be determinant for selecting among new treatment modalities targeting GBM metabolism [56, 57] or monitoring the efficacy of novel immunotherapy approaches [58] beyond conventional chemoradiotherapy [25]. Importantly, DGE-DMI is potentially translatable to high-field clinical MRI scanners, as already demonstrated for DMI at 9.4T [59], benefiting from the higher sensitivity in the much larger human brain compared to mice: 200 cm^3 [60] and 415 mm^3 [61], respectively.

Materials and Methods

Animals and cell lines

All animal experiments were pre-approved by the competent institutional as well as national authorities, and carried out strictly adhering to European Directive 2010/63. A total of n=10 C57BL/6j male mice were used in this study, bred at the Champalimaud Foundation Vivarium, and housed with *ad libitum* access to food and water and 12h light cycles. GL261 mouse glioma cells were obtained from the Tumor Bank Repository at the National Cancer Institute (Frederick MD, USA). CT2A mouse glioma cells were kindly provided by Prof. Thomas Seyfried at Boston College (Boston MA, USA). Both cell lines were grown in RPMI-1640 culture medium supplemented with 2.0 g/l Sodium Bicarbonate, 0.285 g/l L-glutamine, 10% Fetal Bovine Serum (Gibco) and 1% Penicillin-Streptomycin solution. The cell lines tested negative for mycoplasma contamination using the IMPACT Mouse FELASA 1 test (Idexx-BioResearch, Ludwigsburg, Germany).

Glioma models

Tumors were induced in previously described [62]. Briefly, intracranial stereotactic injection of 1 x10^5 GL261 or CT2A cells was performed in the caudate nucleus (n=5 and n=5 mice, respectively); analgesia (Meloxicam 1.0 mg/Kg s.c.) was administered 30 min before the procedure. Mice were anesthetized with isoflurane (1.5-2.0% in air) and immobilized on a stereotactic holder (Kopf Instruments, Tujunga/CA, USA) where they were warmed on a heating pad at 37 °C, while body temperature was monitored with a rectal probe (WPI ATC-2000, Hitchin, UK). The head was shaved with a small trimmer, cleaned with iodopovidone, and the skull exposed through an anterior-posterior incision in the midline with a scalpel. A 1 mm hole was drilled in the skull using a micro-driller, 0.1 mm posterior to the bregma and 2.32 mm lateral to the midline. The tumor cells (1x10^5 in 4 µL PBS) were inoculated 2.35 mm below the cortical surface using a 10 µL Hamilton syringe (Hamilton, Reno NV, USA) connected to an automatic push-pull microinjector (WPI *Smartouch*^{TM}, Sarasota FL, USA), by advancing the 26G needle 3.85 mm from the surface of the skull (~1mm skull-to-brain surface distance), pulling it back 0.5 mm, and injecting at 2 µL/min rate. The syringe was gently removed 2 min after the injection had finished, the skin sutured with surgical thread (5/0 braided silk, Ethicon, San Lorenzo Puerto Rico) and wiped with iodopovidone. During recovery from anesthesia, animals were kept warm on a heating pad and given an opioid analgesic (Buprenorphine 0.05 mg/Kg s.c.) before returning to their cage. Meloxicam analgesia was repeatedly administered at 24- and 48-hours post-surgery.

In vivo Studies

Longitudinal MRI

GBM-bearing mice were imaged every 5-7 days on a 1 Tesla Icon MRI scanner (Bruker BioSpin, Ettlingen, Germany; running *ParaVision 6.0.1* software), to measure tumor volumes. For this, each mouse was placed in the animal holder under anesthesia (1-2 % isoflurane in 31% O_2), heated with a recirculating water blanket, and monitored for rectal temperature (36-37 °C) and breathing (60-90 BPM). Tumor volume was measured with T2-weighted ^{1}H-MRI (*RARE* sequence, ×8 acceleration factor, repetition time TR = 2500 ms, echo time TE = 84 ms, 8 averages, 1 mm slice thickness, and 160×160 µm^2 in-plane resolution), acquired in two orientations (coronal and axial). Each session lasted up to 30 min/animal.

End-point MRI and DMI

GBM-bearing mice with tumors ≥35 mm^3 (longitudinal MRI assessment) were scanned on a 9.4T BioSpec MRI scanner (Bruker BioSpin, Ettlingen, Germany; running under *ParaVision 6.0.1*), using a ^{2}H/^{1}H transmit-receive surface coilset customized for the mouse brain (NeosBiotec, Pamplona, Spain), as described before [31]. Before each experiment, GBM-bearing mice fasted 4- 6h, were weighed, and cannulated in the tail vein with a catheter connected to a home-built 3-way injection

system filled with: 6,6'-$^{2}H_2$-glucose (1.6M in saline); Gd-DOTA (25 mM in saline); and with heparinized saline (10 U/mL). Mice were placed on the animal holder under anesthesia (as in 2.3.1). Coilset quality factors (Q) for ^{1}H and ^{2}H channels were estimated in the scanner for each sample based on the ratio of the resonance frequency (400.34 and 61.45 MHz, for protons and deuterium, respectively) to its bandwidth (full width at half-minimum of the wobbling curve during the initial tuning adjustments): 175±8 and 200±12, respectively. Mice were imaged first with T2-weighted ^{1}H-MRI (*RARE* sequence, x8 acceleration factor, 3000 ms TR, 40 ms TE; 2 averages, 1 mm slice thickness, 70 µm in-plane resolution) in two orientations (coronal and axial). Then, the magnetic field homogeneity was optimized over the tumor region based on the water peak with ^{1}H-MRS (*STEAM* localization: 6x6x3 mm volume of interest, i.e. 108 µL) using localized 1st and 2nd order shimming with the *MapShim Bruker* macro, leading to full widths at half-maximum (FWHM) of 28±5 Hz.

DMI was performed using a *slice-FID chemical-shift imaging* pulse sequence, with 175 ms TR, 256 spectral points sampled over a 1749 Hz window, and Shinnar-Le Roux RF pulse [63, 64] (0.42ms, 10kHz) with 55° flip angle, to excite a brain slice including the tumor: 18×18 mm field- of-view, and 2.27 mm slice thickness. After RF pulse calibration (using the natural abundance semi-heavy water peak, DHO), DGE-DMI data were acquired for 2h23min (768 repetitions), with i.v. bolus of 6,6'-$^{2}H_2$-glucose (2 g/Kg, injected over 30 s; Euroisotop, St Aubin Cedex, France). Data were sampled with an 8×8 matrix and 4-fold Fourier interpolated, rendering a 560 µm in-plane resolution. A reference T2-weighted image was additionally acquired with matching field- of-view and slice thickness, and 70 µm in-plane resolution.

Finally, animals underwent DCE T1-weighted ^{1}H-MRI (*FLASH* sequence, 8° flip-angle, 16ms TR, 4 averages, 150 repetitions, 1 slice with 140 µm in-plane resolution and 2.27 mm thickness, FOV size and position matching the DGE-DMI experiment), with i.v. bolus injection of Gd-DOTA (0.1 mmol/Kg, injected over 30 s; Guerbet, Villepinte, France). Animals were then sacrificed, brains were removed, washed in PBS, and immersed in 4% PFA.

MRI/DMI Processing

T2-weighted ^{1}H-MRI

T2-weighted MRI data were processed in ImageJ 1.53a (Rasband, W.S., ImageJ, U. S. National Institutes of Health, Bethesda, Maryland, USA, *https://imagej.nih.gov/ij/*, 1997-2018). For each animal, the tumor region was manually delineated on each slice, and the sum of the areas multiplied by the slice thickness to estimate the volume, which was averaged across the two orientations acquired (coronal and axial).

DGE-DMI

DGE-DMI data were processed in MATLAB® R2018b (Natick, Massachusetts: The MathWorks Inc.) and jMRUI 6.0b [65]. Each dataset was averaged to 12 min temporal resolution and the central spectral matrix region selected (to discard noise regions outside the brain, as well as the olfactory bulb and cerebellum), rendering a 4D spectral-spatial-temporal matrix of 256×32×32×12 points. After automated phase-correction of each spectrum, the 4D matrix was denoised with a tensor PCA denoising approach [32]. For this, a [8 8 8] window and tensor structure [1 2:3 4] were used for patch processing the spectral, spatial, and temporal dimensions with, whereas the *a priori* average standard deviation of the noise in each spectrum (calculated σ^2) was used to avoid deleterious effects of spatially-correlated noise [34]. Then, these denoised spectra were analyzed voxel-wise by individual peak fitting with AMARES (similarly to the single-spectrum analysis reported previously in [52]), using a basis set for DHO (4.76 ppm: short- and long-T2 fractions [18]) and deuterium-labelled: glucose (Glc, 3.81 ppm), glutamate-glutamine (Glx, 2.36 ppm), and lactate (Lac, 1.31 ppm); relative linewidths referenced to the estimated short- T2 fraction of DHO, according to

the respective T2 relaxation times reported by de Feyter *et al* [18]. The natural abundance DHO peak (DHOi) was further used to select and quantify both original and denoised spectra: SNR_{DHOi} >3.5 and 13.88 mM reference (assuming 80 % water content in the brain and 0.03 % natural abundance of DHO), respectively. Metabolite concentrations (CRLB<50%; otherwise discarded) were corrected for T1 and labeling-loss effects, according to the values reported by de Feyter *et al* (T1, ms: DHO, 320; Glc, 64; Glx, 146; Lac, 297) [18] and de Graaf *et al* (number of magnetically equivalent deuterons: DHO, 1; Glc, 2; Glx, 1.2; Lac, 1.7) [66], respectively. Thus, the concentration of each metabolite (m) at each time point was estimated as (Eq 1):

$$Conc_m = \frac{Area_m - Area0_m}{d_m} \times \frac{C_{DHO}}{C_m} \times \frac{d_{DHO}}{Area0_{DHO}} \times Conc_{ref} \quad \text{(Eq 1)}$$

Area = peak area; *Area0* = average peak area before injection; *d* = number of magnetically equivalent deuterons corrected for labelling-loss effects; *C* = T1 correction factor (1-exp(-TR/T1)); and $Conc_{ref}$ = reference DHO concentration.

The time-course changes of ^{2}H-labelled metabolite (Glc, Glx and Lac) concentrations were fitted using a modified version of the kinetic model reported by Kreis et al [19], to estimate the maximum rate of Glc consumption (total, V_{max}) for Glx synthesis (mitochondrial oxidation, V_{glx}) and Lac synthesis (glycolysis, V_{lac}), and the confidence intervals for all estimated parameters:

$$V_{max} = V_{lac} + V_{glx} \quad \text{(Eq 2)}$$

The coupled differential equations describing the concentration kinetics of each metabolite were:

$$\frac{d[Glc]}{dt} = k_g\left(C_p - \frac{[Glc]}{v}\right) - f\left(\frac{V_{max}[Glc]}{f.v.k_m + [Glc]}\right) \quad \text{(Eq 3)}$$

$$\frac{d[Lac]}{dt} = \frac{fV_{lac}[Glc]}{f.v.k_m + [Glc]} - k_{lac}[Lac] \quad \text{(Eq 4)}$$

$$\frac{d[Glx]}{dt} = \frac{fV_{glx}[Glc]}{f.v.k_m + [Glc]} - k_{glx}[Glx] \quad \text{(Eq 5)}$$

where: k_g, apparent rate constant of glucose transfer between blood and tumor (min^{-1}); k_{glx}, apparent rate constant of Glx elimination (min^{-1}); k_{lac}, apparent rate constant of lactate elimination (min^{-1}); $C_p = a_1 \cdot e^{-kp \cdot t}$, Glc concentration in plasma (mM); a_1, the Glc concentration after the bolus injection (mM); and k_p, the effective rate constant of labeled glucose transfer to tissue (min^{-1}). As reported previously [31], the following parameters were fixed: fraction of deuterium enrichment (*f*), at 0.6 [19]; constant for glucose uptake (k_m), at 10 mM [67, 68]; and the extravascular-extracellular volume fraction (v), at 0.22 – average estimation from DCE-T1-weighted MRI analysis (Table S1). All the other parameters were fitted without any restrictions to their range.

DCE T1-weighted MRI

DCE T1-weighted MRI data were processed with DCE@urLab [69], as before [31]. First, ROIs were manually delineated for each tumor and the time-course data was fitted with the Extended Tofts 2-compartment model [70], to derive the volume transfer constant between plasma and tumor extravascular-extracellular space (k^{trans}), the washout rate between extravascular-extracellular space and plasma (k_{ep}), and the extravascular-extracellular volume fraction (v_e). Then, each dataset was reprocessed by down-sampling the original in-plane resolution to match the DGE-DMI experiment (0.56×0.56×2.27 mm^3), and fitting the time-course data pixel-wise with the Extended Tofts 2-compartment model to derive k^{trans}, k_{ep}, and v_e maps (pixels with root-mean square error >0.005 discarded).

Histopathology and Immunohistochemistry

Whole brains fixed in 4% PFA were embedded in paraffin and sectioned at 30 different levels on the horizontal plane, spanning the whole tumor area. 4 µm sections were stained with H&E (Sigma-Aldrich, St. Louis MO, USA), digitized (Nanozoomer, Hamamatsu, Japan), and analyzed by an experimental pathologist blinded to experimental groups, according to previously established criteria [31]. Then, QuPath v0.4.3 built-in tools [71] were used to highlight different tumor regions: Tumor ROIs, corresponding to the bulk tumor, were delineated first with "create threshold" and then manually corrected; Border ROIs, including areas of peritumoral infiltration, were delineated with "expand annotations" by expanding 100 µm the tumor margin toward the adjacent brain parenchyma; Infiltrative ROIs, corresponding to specific infiltrative regions, were manually annotated. Between 3 to 6 sections of each tumor were also immunostained for Ki67 (mouse anti-ki67, BD, San Jose CA, USA; blocking reagent, M.O.M ImmPRESS kit, Vector Laboratories, Burlingame CA, USA; liquid DAB$^+$, Dako North America Inc, Carpinteria CA, USA), digitized (Nanozoomer, Hamamatsu, Japan), and analyzed with QuPath built-in tools [71] for Tumor and Border ROIs, defined as detailed above. Thus, Ki67$^{+/-}$ cells were counted semi-automatically to determine the total number of cells, the cell density, and the proliferation index (% Ki67$^+$ cells) as the average across slices for each ROI, and respective tumor/border ratios. This procedure was repeated for each animal.

Statistical analyses

Data were analyzed in MATLAB® R2018b (Natick, Massachusetts: The MathWorks Inc.) using the two-tailed Student's *t*-test, either unpaired (comparing different animal cohorts) or paired (comparing the same animal cohort in different conditions). Differences at the 95% confidence level (p=0.05) were considered statistically significant. Correlation analyses were carried out with the Pearson R coefficient. Error bars indicate standard deviation unless indicated otherwise.

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Editors

Reviewing Editor
Sameh Ali
Children's Cancer Hospital Egypt, Cairo, Egypt

Senior Editor
Tony Ng
King's College London, London, United Kingdom

Reviewer #1 (Public Review):

Summary:

This work introduces a new imaging tool for profiling tumor microenvironments through glucose conversion kinetics. Using GL261 and CT2A intracranial mouse models, the authors demonstrated that tumor lactate turnover mimicked the glioblastoma phenotype, and differences in peritumoral glutamate-glutamine recycling correlated with tumor invasion capacity, aligning with histopathological characterization. This paper presents a novel method to image and quantify glucose metabolites, reducing background noise and improving the predictability of multiple tumor features. It is, therefore, a valuable tool for studying glioblastoma in mouse models and enhances the understanding of the metabolic heterogeneity of glioblastoma.

Strengths:

By combining novel spectroscopic imaging modalities and recent advances in noise attenuation, Simões et al. improve upon their previously published Dynamic Glucose-Enhanced deuterium metabolic imaging (DGE-DMI) method to resolve spatiotemporal glucose flux rates in two commonly used syngeneic GBM mouse models, CT2A and GL261. This method can be standardized and further enhanced by using tensor PCA for spectral denoising, which improves kinetic modeling performance. It enables the glioblastoma mouse model to be assessed and quantified with higher accuracy using imaging methods.

The study also demonstrated the potential of DGE-DMI by providing spectroscopic imaging of glucose metabolic fluxes in both the tumor and tumor border regions. By comparing these results with histopathological characterization, the authors showed that DGE-DMI could be a powerful tool for analyzing multiple aspects of mouse glioblastoma, such as cell density and proliferation, peritumoral infiltration, and distant migration.

Weaknesses:

Although the paper provides clear evidence that DGE-DMI is a potentially powerful tool for the mouse glioblastoma model, it fails to use this new method to discover novel features of tumors. The data presented mainly confirm tumor features that have been previously reported. While this demonstrates that DGE-DMI is a reliable imaging tool in such circumstances, it also diminishes the novelty of the study.

When using DGE-DMI to quantitatively map glycolysis and mitochondrial oxidation fluxes, there is no comparison with other methods to directly identify the changes. This makes it difficult to assess how sensitive DGE-DMI is in detecting differences in glycolysis and mitochondrial oxidation fluxes, which undermines the claim of its potential for in vivo GBM phenotyping.

The study only used intracranial injections of two mouse glioblastoma cell lines, which limits the application of DGE-DMI in detecting and characterizing de novo glioblastomas. A de novo mouse model can show tumor growth progression and is more heterogeneous than a cell line injection model. Demonstrating that DGE-DMI performs well in a more clinically relevant model would better support its claimed potential usage in patients.

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Reviewer #2 (Public Review):

Summary:

In this work, the authors attempt to noninvasively image metabolic aspects of the tumor microenvironment in vivo, in 2 mouse models of glioblastoma. The tumor lesion and its surrounding appearance are extensively characterized using histology to validate/support any observations made with the metabolic imaging approach. The metabolic imaging method builds on a previously used approach by the authors and others to measure the kinetics of deuterated glucose metabolism using dynamic 2H magnetic resonance spectroscopic imaging (MRSI), supported by de-noising methods.

Strengths:

Extensive histological evaluation and characterization.

Measurement of the time course of isotope labeling to estimate absolute flux rates of glucose metabolism.

Weaknesses:

The de-noising method appears essential to achieve the high spatial resolution of the in vivo imaging to be compatible with the dimensions of the tumor microenvironment, here defined as the immediately adjacent rim of the mouse brain tumors. There are a few challenges with this approach. Often denoising methods applied to MR spectroscopy data have merely a cosmetic effect but the actual quantification of the peaks in the spectra is not more accurate than when applied directly to original non-denoised data. It is not clear if this concern is applicable to the denoising technique applied here. However, even if this is not an issue, no denoising method can truly increase the original spatial resolution at which data were acquired. A quick calculation estimates that the spatial resolution of the 2H MRSI used here is 30-40 times too low to capture the much smaller tumor rim volume, and therefore there is concern that normal brain tissue and tumor tissue will be the dominant metabolic signal in so-called tumor rim voxels. This means that the conclusions on metabolic features of the (much larger) tumor are much more robust than the observations attributed to the (much smaller) tumor microenvironment/tumor rim.

To achieve their goal of high-level metabolic characterization the authors set out to measure the deuterium labeling kinetics following an intravenous bolus of deuterated glucose, instead of the easier measurement of steady-state after the labeling has leveled off. These dynamic data are then used as input for a mathematical model of glucose metabolism to derive fluxes in absolute units. While this is conceptually a well-accepted approach there are concerns about the validity of the included assumptions in the metabolic model, and some of the model's equations and/or defining of fluxes, that seem different than those used by others.

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Reviewer #3 (Public Review):

Summary:

Simoes et al enhanced dynamic glucose-enhanced (DGE) deuterium spectroscopy with Deuterium Metabolic Imaging (DMI) to characterize the kinetics of glucose conversion in two murine models of glioblastoma (GBM). The authors combined spectroscopic imaging and noise attenuation with histological analysis and showcased the efficacy of metabolic markers determined from DGE DMI to correlate with histological features of the tumors. This approach is also potent to differentiate the two models from GL261 and CT2A.

Strengths:

The primary strength of this study is to highlight the significance of DGE DMI in interrogating the metabolic flux from glucose. The authors focused on glutamine/glutamate and lactate. They attempted to correlate the imaging findings with in-depth histological analysis to depict the link between metabolic features and pathological characteristics such as cell density, infiltration, and distant migration.

Weaknesses:

(1) A lack of genetic interrogation is a major weakness of this study. It was unclear what underlying genetic/epigenetic aberrations in GL261 and CT2A account for the metabolic difference observed with DGE DMI. A correlative metabolic confirmation using mass spectrometry of the two tumor specimens would give insight into the observed imaging findings.

(2) A better depiction of the imaging features and tumor heterogeneity would support the authors' multimodal attempt.

(3) Integration of the various cell types in the tumor microenvironment, as allowed with the resolution of DGE DMI, will explain the observed difference between GL261 and CT2A. Is there a higher percentage of infiltrative "other cells" observed in GL261 tumor?

(4)This underlying technology with DGE DMI is capable of identifying more heterogeneous GBM tumors. A validation cohort of additional in vivo models will offer additional support to the potential clinical impact of this study.

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