

Advances in mass spectrometry-enabled multiomics analyses at single-cell resolution

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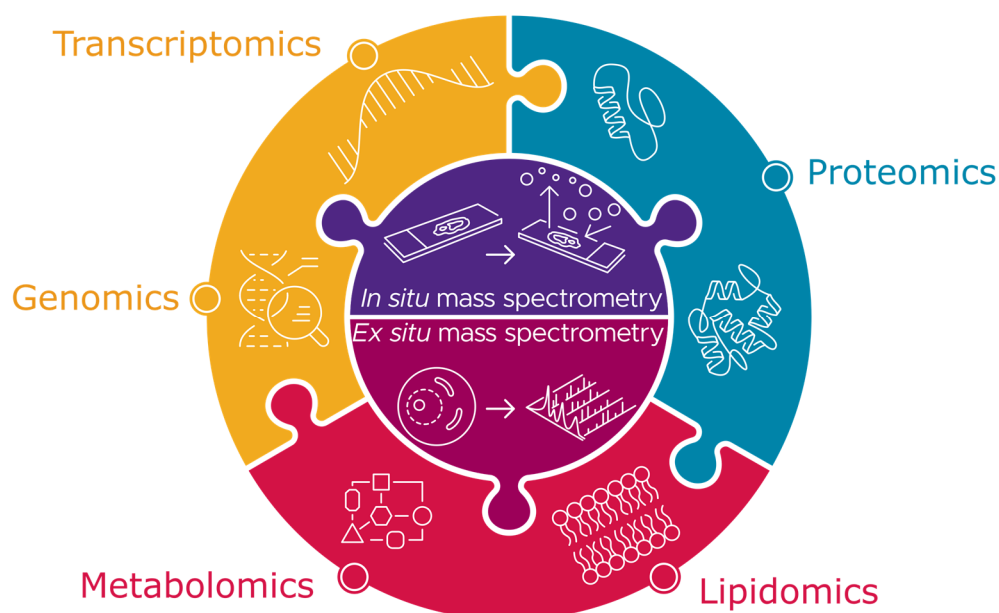
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Abstract Biological organisms are multifaceted, intricate systems where slight perturbations can result in extensive changes in gene expression, protein abundance and/or activity, and metabolic flux. These changes occur at different timescales, spatially across cells of heterogenous origins, and within single cells. Hence multimodal measurements at the smallest biological scales are necessary to capture dynamic changes in heterogenous biological systems. Of the analytical techniques used to measure biomolecules, mass spectrometry has proven to be a powerful option due to its sensitivity, robustness, and flexibility with regards to breadth of biomolecules that can be analyzed. Recently many studies have coupled mass spectrometry to other analytical techniques with the goal of measuring multiple modalities from the same single-cell. It is with these concepts in mind that we focus this Review on mass spectrometry-enabled multiomic measurements at single cell or near single cell resolution.

Graphical Abstract

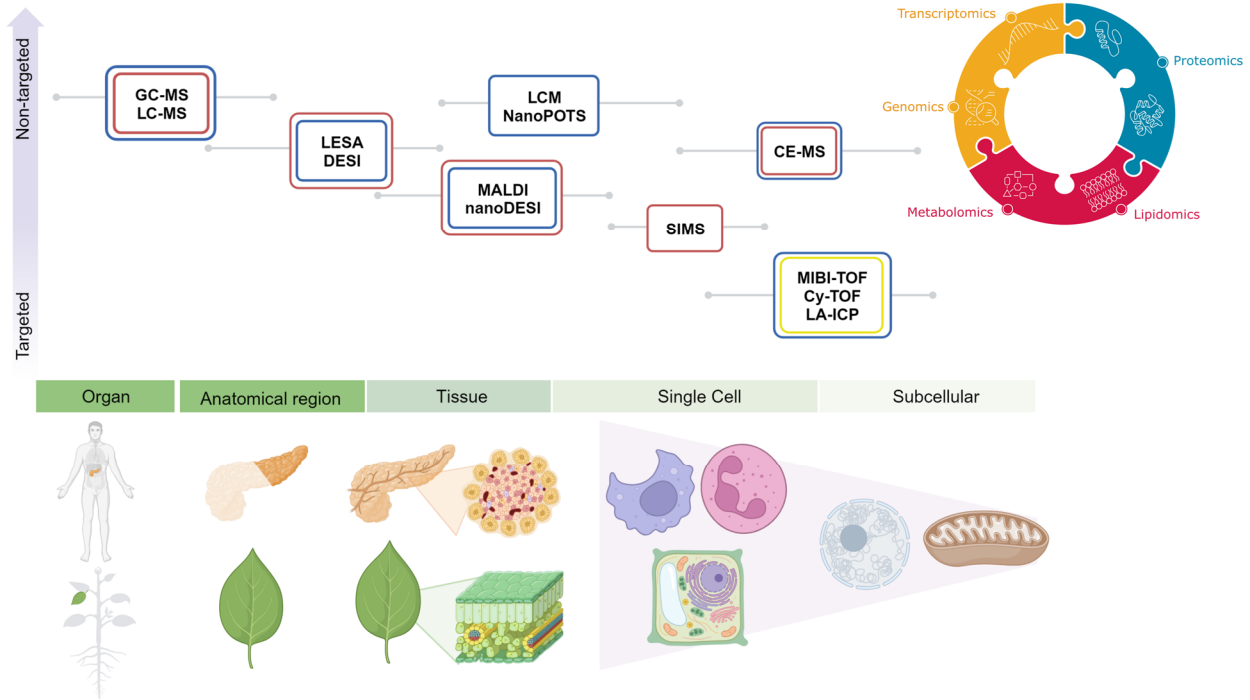


20 **Introduction**

21 Understanding health and disease mechanisms in animals, plants and microbes requires a
22 systems-level investigation of regulatory networks at the levels of genes, transcripts, proteins, and
23 metabolites. The majority of multiomic studies performed to date have been bulk analyses on blood[1],
24 plasma[2], cell pellets[3] or whole tissues. While bulk analyses are often cost effective and
25 technologically less demanding, such analyses cannot measure cell heterogeneity and biologically
26 significant rare cell populations are often missed. Several ongoing initiatives, with a loosely shared goal
27 of characterizing tissues at single-cell resolution, such as the Human Biomolecular Atlas Program
28 (HuBMAP)[4], Human Tumor Atlas Network (HTAN)[5], Kidney Precision Medicine Project
29 (KPMP)[6], Human Cell Atlas[7], and Cellular Senescence Network (SenNet)[8] are supporting the
30 development of novel single-cell -omic techniques. Recently developed single-cell RNA sequencing
31 (scRNAseq) techniques have revolutionized our understanding of developmental trajectories,[9] identified
32 new cell types,[10] and enabled the mapping of entire organs.[11] Towards holistic understanding of
33 biological processes, these sequencing methods have also been extended to multimodal measurements
34 from the same single-cells.[12][13]

35 Although sequencing-based -omic approaches have many advantages (e.g., fidelity, cost, and
36 throughput), there are limitations for protein measurements (e.g., intermediate antibody probes and
37 limited access to intracellular targets)[14–16] and metabolites/lipids cannot be directly measured.
38 Fortunately, it is within these classes of molecules that mass-spectrometry (MS) thrives, demonstrated by
39 decades of studies performed at tissue scale. Recent advancements in MS techniques have pushed the
40 envelope further, enabling cellular and subcellular measurements. When combined with orthogonal
41 techniques, measurements across modalities from same single cells becomes possible.[17] It is with this
42 in mind that we focus this Review on same single-cell (or near single-cell) MS-enabled multiomics.

43 **State-of-the-art approaches**



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Figure 1. Overview of mass spectrometry approaches (both *in situ* and *ex situ*) applied to multimodal analyses. The color of the box surrounding each technique represents modalities measured (reflected in the upper right corner), while spatial resolution is reflected along the x-axis and breadth of molecular coverage (targeted to non-targeted) along the y-axis. Figure created with Biorender.com

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Significant technological advances in MS over the past decades have enabled single-cell and even

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subcellular analyses (**Figure 1**). These techniques with single cell or near single cell resolution can

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broadly be classified as 1) *In situ* or 2) *Ex situ* MS-enabled single-cell multiomics.

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Techniques classified under *in situ* are largely based on MS imaging (MSI), which directly analyzes

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biomolecules from thin tissue sections to retain spatial context. On the other hand, *ex situ* techniques

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largely require removal of single cells from their spatial context. These techniques often include the use

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of chromatographic separations on extracted single-cells prior to MS analysis. Further distinction of

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multimodal MSI applications can be made regarding the breadth of measurements, which we refer to as

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“targeted” or “non-targeted”.[18] These terms refer to the number of features being measured, with

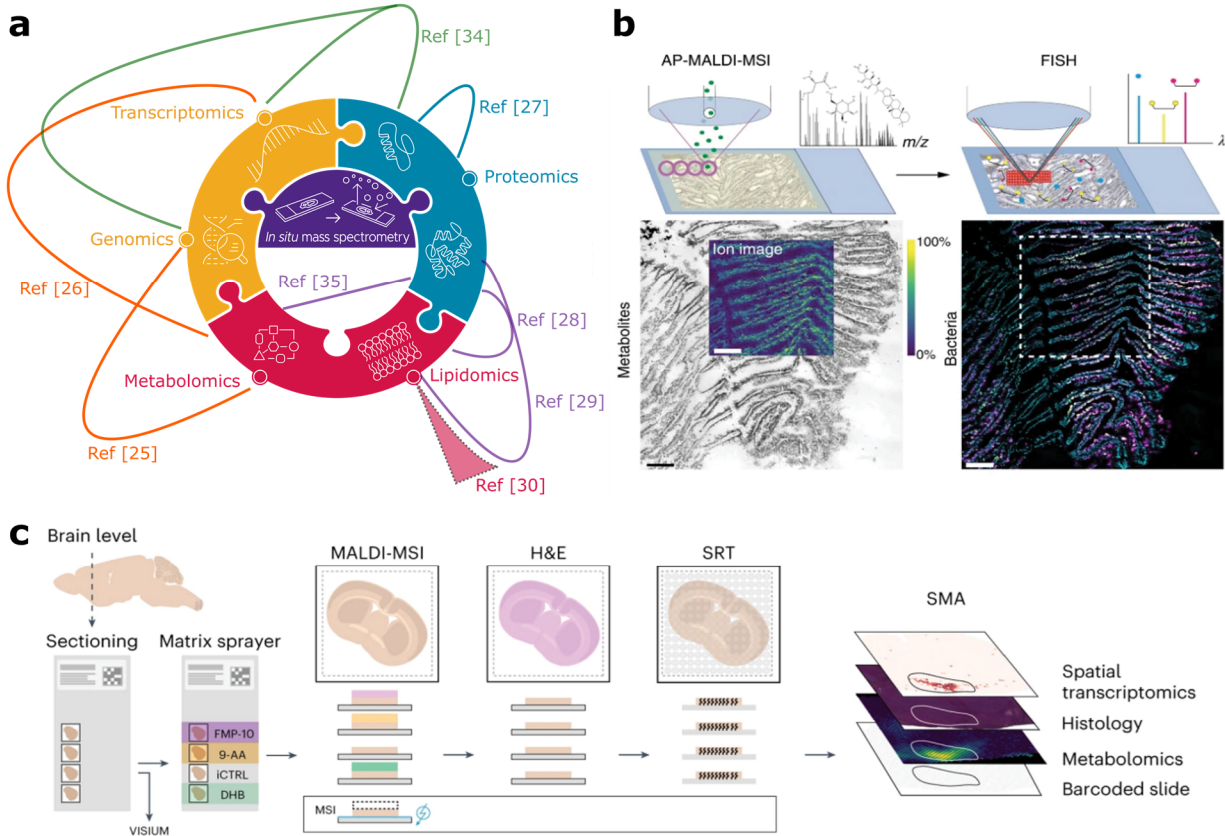
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targeted approaches typically focusing maximally on several dozen or fewer biomolecules and non-

55 targeted capturing hundreds or thousands (**Figure 1**). Also, note that several MS-only MSI techniques
56 exist that can measure multiple modalities simultaneously or sequentially (such as matrix-assisted laser
57 desorption/ionization [MALDI] and gas cluster ion beam secondary ion MS [GCIB-SIMS]), [19–21]
58 however the principal focus in this Review is on MS techniques alone or combined with orthogonal, non-
59 MS methods for measuring multiple biomolecules with single-cell or near single-cell resolution.

60 ***In situ* MS-enabled single-cell multiomics**

61 Numerous *in situ* MS-enabled multimodal approaches have recently been demonstrated at single-
62 cell or near single-cell resolution on the same sample (**Figure 2a** and **Table S1**; a summary of MSI-
63 enabled multiomics studies performed on different samples is also presented in **Figure S1**). Among MSI
64 techniques at single-cell level, MALDI is the most versatile, having been widely used for the analysis of
65 proteins, glycans, peptides, lipids, and metabolites.[22,23] It should be noted, however, that there is an
66 inverse relationship between analyte size/ionizability and sensitivity with MALDI. For example,
67 metabolites are routinely detected at trace amounts (low attomole)[24] whereas intact proteins typically
68 have limits of detection orders of magnitude higher. Furthermore, sensitivity is intrinsically tied to the
69 spatial resolution, where lower resolution (e.g., 100 μm) is more sensitive than high spatial resolution
70 (e.g., 10 μm) due to the size of the area being sampled. Last, MALDI-MSI is completed at modest spatial
71 resolutions of 5-50 μm and in a non-targeted manner.



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Figure 2. Summary and examples of *in situ* mass spectrometry-enabled single-cell multiomics. **(a)** Chord diagram showing the connections (*i.e.* studies) between modalities enabled by *in situ* techniques. **(b)** Left panel; MALDI-MSI metabolite mapping of bacteriocyte-containing deep-sea mussel *Bathymodiolus puteoserpentis* cryosection. Ion image is overlaid onto bright-field image of the same cryosection. Right panel; FISH after MALDI-MSI on the same cryosection. Colors indicate host nuclei (cyan) and two bacteriocyte phylotypes (magenta and yellow). **(c)** Overview of spatial multimodal analysis (SMA) showing cyrosectioning onto barcoded Visium Gene Expression arrays. **(b)** Reprinted with permission from Figure 1a-b in Ref. [25]. Copyright 2020 Springer Nature. **(c)** Reprinted with permission from Figure 1a in Ref [26]. Copyright 2023 Springer Nature

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Co-measuring of genomes and metabolomes from the same section have been demonstrated with

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non-targeted MALDI-MSI (spatial resolution of 3 μm) and FISH (termed metaFISH, **Figure 2b**),

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providing greater understanding of host/symbiont relationships between deep-sea mussel and their

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intracellular bacteria.[25] Another recent study demonstrated MALDI-MSI based metabolomics and

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spatial transcriptomics on the same tissue sections by mounting them on the Visium Spatial Gene

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Expression array, performing MALDI-MSI metabolomics, and finally spatial transcriptomics with

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Visium (**Figure 2c**).[26] This technique, termed spatial multimodal analysis (SMA) protocol, enabled the

80 identification of unique spatial correlations between dopamine and mRNA from *SCG2* in mouse and
81 human brain samples. Notably, SMA is currently the only MSI enabled multimodal approach at near
82 single cell resolution where both modalities are non-targeted.

83 MALDI-MSI can be also used to map post translational modifications such as N-glycans in
84 combination with spatial analysis of target proteins. In a recent study, systematic optimization was done
85 for sequential MALDI-MSI imaging of N-glycans or collagen peptides (non-targeted), AmberGen
86 photocleavable mass-tags (MALDI technique leveraging photocleavable mass tags on antibodies,
87 targeted), imaging mass cytometry (IMC, targeted), and GeoMx digital spatial profiling (targeted).[27]
88 This study is noteworthy because the authors demonstrated the compatibility of MALDI-MSI with
89 antibody-directed techniques and determined optimal order of different techniques for achieving greatest
90 sensitivity. Similarly, MALDI-MSI based lipidomics has also been combined with protein measurements
91 such as antibody-based fluorescence imaging techniques (*i.e.* CODEX) on same tissue sections or with
92 immunocytochemistry on dispersed cells.[28][29] Finally, MALDI-MSI of lipids has also been
93 sequentially combined with Raman spectroscopy (which identifies functional groups as biomolecular
94 fingerprints) in the analysis of same kidney and brain tissue sections.[30] Although Raman cannot
95 provide annotations of molecules in complex mixtures such as tissue, this approach uniquely allowed for
96 correlation between MALDI-MSI lipid species and Raman spatial patterns to identify similar
97 distributions. Taken together, these studies demonstrate the versatility of non-targeted MALDI-MSI in
98 single-cell, multimodal data acquisition.

99 Targeted MSI techniques include imaging mass cytometry (IMC), nanoSIMS, multiplexed ion
100 beam imaging by time-of-flight (MIBI-TOF), and laser ablation inductively coupled MS (LA-ICP).
101 Applications of these techniques typically involves the addition of an antibody, oligo probe, or ligand
102 labeled with heavy elements (e.g., lanthanides) to provide a secondary measurement of the analyte of
103 interest. Notably, the use of these ionization methods and elemental measurements have some of the
104 highest spatial resolution (submicron) and sensitivity (down to 5 atom detection limit),[31] however they

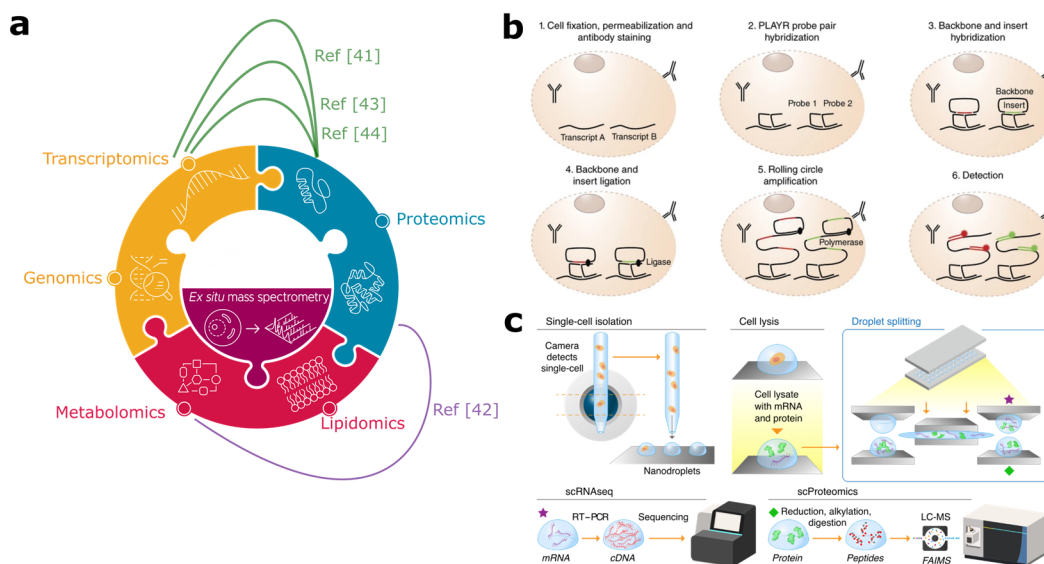
105 are often restricted to targeted elemental isotope analysis to infer molecular identifications.[32,33] Protein
106 and nucleic acid *in situ* imaging (PANINI), which uses the MIBI-TOF imaging platform, was shown to be
107 compatible with CODEX. The PANINI technique provided the ability to measure simian
108 immunodeficiency virus DNA and RNA alongside host immune protein markers in FFPE tissues.[34]

109 The above approaches all rely on MSI; however, a recently developed *quasi in situ* approach
110 permits *in vivo* microsampling. Microsampled lysates can be analyzed with downstream chromatographic
111 techniques for non-targeted multimodal analyses. Specifically, this approach has been demonstrated with
112 *Xenopus laevis* embryos that were microsampled to withdraw ~5% of cellular volume before downstream
113 proteometabolomic analysis with ultrasensitive capillary electrophoresis MS.[35] With as little as 0.01%
114 of the cell's volume, 738 proteins and ~150 metabolite features could be identified per single-cell.
115 Although *X. laevis* embryo cells are very large (180 nL volume / cell in the 8-cell embryo), there are
116 several notable advantages to this approach. First, microsampling is relatively non-destructive and permits
117 early-stage embryos to continue development into later stages. Second, because every cell in early-stage
118 embryos can be identified based on pigmentation, microsampling permits sampling of specific cells with
119 distinct trajectories. Therefore, microsampling is uniquely a subcellular, spatiotemporal method for
120 sampling from embryo cells without impacting their viability.

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122 **Ex situ MS-enabled single-cell multiomics**

123 Single-cell multimodal studies that utilize *ex situ* MS typically include downstream
124 chromatographic methods, and therefore have a different set of challenges that have limited widespread
125 adoption (**Figure 3a**).



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Figure 3. Summary and examples of *ex situ* MS-enabled single-cell multiomics. (a) Chord diagram showing the connections (studies) between modalities enabled by *ex situ* techniques. (b) Overview of the PLAYR protocol showing the major steps before FACS and CyTOF measurements of single-cells. (c) Overview of the nanoSPLITS multiomics approach

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127 The sampling of biomolecules from single-cells required for these techniques often leads to the loss of
128 analytes due to non-specific surface adsorption.[36] Fortunately, recently developed microfluidic
129 techniques for manipulating picoliter to nanoliter volumes have helped to overcome these issues[37,38].
130 Furthermore, the last few decades have seen significant improvements in MS -omics data analysis tools,
131 sample preparation, and large increases in MS analyzer sensitivity making MS-enabled single-cell -omics
132 feasible.[35,37,39] Nanoflow reverse phase liquid chromatography (RPLC) and capillary electrophoresis
133 (CE) are most common liquid phase separation methods for single-cell omics. Detection of peptides from
134 as little as 700 zmol have been demonstrated with CE-ESI, [35] and nanoflow RPLC has been

135 demonstrated down to 30 zmol.[40] In some demonstrations, *ex situ* MS-enabled multiomics can be
136 performed directly on single-cells, thereby avoiding issues related to analyte loss during handling.

137 One such technique that has utilized sorted cells directly is proximity ligation assay for RNA
138 (PLAYR), a targeted RNA and protein technique that permits simultaneous measurements through mass
139 cytometry (**Figure 3b**).[41] PLAYR utilized permeabilized cells labeled with metal-conjugated antibodies
140 and metal-conjugated oligonucleotides to simultaneously quantify targeted protein and mRNA molecules,
141 respectively. Generally, CyTOF multiplexing is limited to a maximum of 50 targets. Another multimodal
142 study utilized specialized microwells with polyethylene glycol-modified surfaces to divide metabolites
143 and proteins from smaller single-cells through differential adsorption for downstream non-targeted
144 analysis by ESI-MS.[42] This strategy enabled quantitation of 132 metabolites and over 1,200 proteins
145 from same single-cells.

146 The combination of non-targeted scRNAseq with non-targeted MS-based scProteomics has also
147 been an area of recent development. Two such techniques have been demonstrated thus far: single-cell
148 simultaneous transcriptome and proteome (scTAP)[43] analysis and nanodroplet splitting for linked-
149 multimodal Investigations of trace samples (nanoSPLITS)[44]. scTAP has been demonstrated with single
150 oocytes by splitting the cell lysate using a capillary probe. This enables half of the lysate to be analyzed
151 with LC-MS/MS proteomics and the other half to be analyzed with RNA sequencing. With the scTAP
152 technique 19,948 genes and 2,663 proteins on average could be identified from single mouse oocytes.
153 However, throughput of scTAP is limited and has not been demonstrated in cultured or primary cells,
154 which are considerably smaller in size and molecular content than oocytes. Alternatively, nanoSPLITS
155 was also recently developed for co-measuring the transcriptome and proteome from same single-cells
156 (**Figure 3c**).[44] The nanoSPLITS approach is accomplished by sorting single-cells onto a nanodroplet
157 array that contain a mild permeabilization buffer, after which a separate array of blank droplets without
158 cells is brought in proximity to enable merging and splitting of the cell lysates, thus allowing for parallel
159 scRNAseq and scProteomics. The nanoSPLITS approach confidently identified and quantified ~5000

160 genes (using scRNAseq Smart Seq) and ~3000 proteins (using nanoPOTS-based LC-MS proteomics)
161 from cultured single-cells.[44]

162 **Prospects and Conclusion**

163 MS-enabled multimodal studies performed on same single cells or same tissue sections are still in
164 their infancy. When considering MS-only multimodal studies, *in situ* MSI approaches have seen
165 considerably more single-cell or near single-cell applications relative to *ex situ* MS techniques. As MSI
166 retains spatial context, this begs the question why are *ex situ* MS techniques needed? One answer lies in
167 the quantitative limitations of MALDI (e.g., ionization biases across all ionizable molecules),[45] and the
168 need for intermediate antibodies or probes for other MSI techniques. It is also interesting to note that
169 many MSI multiomic studies rely on consecutive tissue sections to measure different modalities. As each
170 tissue section is essentially composed of different cells, many of the casual relationships between
171 biomolecules will be lost. Furthermore, image alignment and co-registration are non-trivial, further
172 reducing the connectedness between modalities. Fortunately, recent studies have begun to optimize and
173 integrate disparate sample preparation methods to achieve multimodal measurements on the same tissue
174 section[26–28]. We anticipate this trend will continue to grow, and ideally obviate the need for
175 consecutive tissue sectioning in the future for performing multiomics.

176 **Figures 2a** and **3a** suggest that connections between some modalities are more represented than
177 others. Particularly for *ex situ* MS approaches, multimodal lipid measurements are underrepresented. One
178 reason may be that *ex situ* techniques enabling single-cell lipidomics only recently become available.
179 [46,47] It is also noteworthy that no studies have yet accomplish measuring all three major classes of
180 biomolecules in a non-targeted manner from the same single-cell using MS methods alone or in
181 combination with other methods. Such a feat, if performed in high enough throughput, would
182 undoubtedly prove useful for modeling of cellular processes. Conceivably, techniques that sample a
183 portion of the cellular contents (such as scTAP, nanoSPLITS, and microsampling) could be extended to
184 include additional modalities. The MS-enabled non-targeted scRNAseq approaches are also notable due

185 to the utility of transcriptomics data with assigning cell types in heterogenous populations. The past few
186 years have seen an explosion in large scale scRNAseq studies that have provided millions of cells for
187 reference mapping across almost all major organs in human and mouse, and even whole model organisms
188 such as *C. elegans*. [48,49] In cases where such data is available, these reference maps provide incredible
189 power for discriminating cell types due to the clustering across large, diverse populations of cells which
190 often cannot be easily accomplished in other modalities such as proteomics. Furthermore, by relying on
191 one modality (e.g., transcriptomics) to cluster and determine cell types, the other modality is free from
192 statistical “double dipping” that inflates false positives when trying to cluster and perform differential
193 expression analysis on the same data. [50]

194 In this Review, we have focused on single-cell or near single-cell MS-enabled multimodal studies
195 alone or in combination with orthogonal techniques for comprehensive understanding of biological
196 systems. MS-based approaches provide excellent orthogonality to sequencing in the context of discovery-
197 based experiments at the single-cell level, and studies discussed in this review have successfully exploited
198 these different approaches to great effect. As this field is still in its infancy, we anticipate the next decade
199 will experience significant progress and innovation leading to novel discoveries enabled by MS-enabled
200 single cell multiomics.

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