² π -HuB: The Proteomic Navigator of The Human Body

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1 Abstract

The human body contains trillions of cells, classified in specific cell types, diverse morphologies and 2 functions. Additionally, cells of the same type can assume different states within an individual's body during 3 their lifetime. Understanding the complexities of the proteome in the context of a human organism and its 4 many potential states is a necessary requirement to understand human biology, but these complexities can 5 6 neither be predicted from the genome, nor have they been systematically measurable with available 7 technologies. Recent advances in proteomic technology and computational sciences now provide opportunities to investigate the intricate biology of the human body at unprecedented resolution and scale. 8 9 Here, we introduce a big-science endeavor called π -HuB (Proteomic Navigator of the Human Body). The 10 ultimate aim of the π -HuB project is to generate and harness multi-modality proteomic datasets to enhance 11 our understanding of human biology, to facilitate disease risk assessment, diagnosis, to uncover new drug targets, to optimize appropriate therapeutic strategies, and to enable intelligent healthcare, thereby ushering 12 in a new era of proteomics-driven phronesis medicine. This ambitious mission will be implemented by an 13 international collaborative force of multidisciplinary research teams worldwide across academic, industrial 14 and government sectors. 15

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1 Introduction

The Human Genome Project (HGP) provided a comprehensive map of the human genome and identified 2 the specie's $\sim 20,300$ protein coding genes^{1,2}. It demonstrated the power of data-driven, large-scale 3 coordinated 'omics' projects in transforming biomedical research, giving rise to genomics-driven precision 4 5 medicine (GDPM). The human body contains approximately 37 trillion cells of distinctive types, diverse 6 morphologies and functions, organized in tissues and organs, all of which share essentially the same genome. 7 Moreover, during individuals' lifetime, tissues/organs and cells within their bodies have often undergone 8 extensive or reversible/irreversible changes in response to changing conditions. The experience over the 9 approximately 24 years since the publication of the human genome sequence has shown that the observed 10 cellular and organismic complexities cannot be predicted from the genomic information alone.

11 Human biology, with all its intricate complexities, is profoundly interconnected with the vast expanse that is often termed the protein 'universe' or, more scientifically, the proteome (the complete set of proteins 12 13 expressed by a genome in any cell or tissue at a specific point in time)³. Serving as the fundamental functional elements of cellular mechanisms, proteins are involved in essentially any biological process 14 15 within an organism. Their significance extends beyond normal physiology; proteins have been crucially 16 implicated as major contributors to the onset and progression of various diseases. They emerge as central figures in the field of therapeutics, being the primary molecular targets for a large majority of drugs. Hence, 17 far beyond the static view provided by genomics, proteomics provides information about the dynamic 18 aspects of the human body and its adaption to changing conditions. Following the HGP era, research based 19 20 on the human proteome is one of the most exciting, yet challenging topics in life sciences and medicine^{4,5}. In 2001, coinciding with the publication of the human genome sequence, a group of proteomics 21 researchers founded the International Human Proteome Organization (HUPO)⁶. In September 2010, HUPO 22

23 took the first step towards an international collaborative effort, termed the Human Proteome Project (HPP), to find high-quality evidence for the expression of all human protein-coding genes using mass spectrometry 24 25 (MS) and making them routinely and reliably measurable. Since then, HUPO has stimulated and 26 coordinated many workshops to work in the HPP. Ten years later in 2020, the HUPO HPP project teams 27 described the first high-stringency HPP proteome map, covering 90.4% of the canonical human proteome, 28 paralleling similar decadal progress made by the HGP⁷. By 2023, detection of 18,397 (93%) of the predicted 29 19,750 canonical proteins encoded in the human genome had been achieved⁸ and a compendium of validated reference spectra for the highly specific targeted mass spectrometric measurement >99% of the 30 annotated human proteins had been generated⁹. Since the formation of HUPO, there has been an expansion 31 of biology/disease-centric initiatives under the HPP umbrella. These aim to spatially measure and interpret 32 33 human proteome data under a range of physiological and pathological conditions, including protein 34 abundance, post-translational modifications, interaction partners, and localization.

The first proteomics project dedicated to a human organ (Human Liver Proteome Project, HLPP) was 1 actually launched in China in 2003, much before, and as a forerunner of, the HPP¹⁰⁻¹². This led to the 2 characterization of liver protein expression profiles and protein-protein interactions in this metabolic 3 organ¹³, as well as the discovery of a major functional role of acetylation in metabolic regulation^{14,15}. 4 Subsequently, the proteomes of other tissues or organs (e.g., brain¹⁶, heart¹⁷, stomach¹⁸, skin¹⁹, and immune 5 cells²⁰) have been characterized, creating an initial version of the organ/tissue-based human proteome 6 map^{21,22}. Meanwhile, an increasing number of disease-related organ/tissue proteomes have been analyzed 7 as exemplified by the Chinese Human Proteome Project (CNHPP)²³, the National Cancer Institute's Clinical 8 Proteomic Tumor Analysis Consortium (CPTAC) in the United States²⁴, the Tumor Profiler Project (TuPro) 9 in Switzerland²⁵, the Human Protein Atlas in Sweden^{26,27}, and ProCan in Australia²⁸. Moreover, recent 10 advances in non-MS based approaches provide versatile opportunities for biomarker discovery in body 11 fluids, which is thought to reflect a person's health or disease status²⁹⁻³¹. All these efforts are providing a 12 significant boost in advancing the field toward an era that has previously been termed PDPM (proteomics-13 driven precision medicine)³². Despite remarkable technological and computational advances, we are only 14 just beginning the exploration of the complexities of the human proteome, and the exploitation of the full 15 potential of the proteome for biomedical breakthroughs has yet to be fully harnessed (Box 1). 16

17 In 2020, the Chinese Ministry of Science and Technology funded a collaboration of around 40 proteomics 18 research teams worldwide to envision future HPP-related projects. Since then, several multidisciplinary 19 working groups have been established, and numerous on-site meetings and webinars have been organized, 20 which have been communicated with government and private funding bodies. These activities have allowed 21 us to propose a big science project called π -HuB (Proteomic Navigator of the Human Body). The project is 22 forming a consortium of Chinese and international scientists to generate mega proteomic datasets from all major human tissues/organs and cell types, and to subject the data to integrative analysis at an 23 unprecedented scale. The ultimate aim is to build an intelligent computational engine called the π -HuB 24 navigator which will integrate multi-modality proteomic datasets to enhance our understanding of human 25 biology, to facilitate disease risk assessment, diagnosis, to uncover new drug targets, to optimize appropriate 26 27 therapeutic strategies, and to enable intelligent healthcare.

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29 Three Central Goals of the π -HuB Project

The π -HuB project has the overriding mission, to support, with an investment of billions of RMB, the international and interdisciplinary collaboration of scientists for a period of three decades towards three specific goals (Fig. 1).

33 *1. Discover principles of the human body* The π -HuB project will first dissect the human body into a 34 hierarchy of digital proteomic anatomy spaces. By harnessing rapidly evolving techniques such as single-

cell and spatial proteomics 33,34 , the project will digitize, and continually refine, the complete quantitative 1 2 proteomic and cellular composition of the human body, including cell composition of all major 3 tissues/organs, protein composition of individual cell types and single cells, and proteome-centric molecular networks within cells (e.g., PTMs, PPIs). Taking advantage of recent advances in multi-modal data 4 5 fusion/integration technology, in particular, the rapid development of deep learning or foundational models, the high-resolution anatomy-based proteomic data will provide an unprecedented opportunity to decode the 6 7 essential molecular/cellular building principles of cells/tissues/organs, and to uncover the critical molecular/cellular mechanisms of biological processes, i.e. to reveal causal relations from a protein network 8 9 to a phenotype.

10 2. Develop the Meta Homo Sapiens model The π -HuB project will conduct in-depth investigations into the dynamics of the human proteome throughout an individual's lifespan, exploring at a population 11 level how the human proteome adapts in response to various factors impacting health outcomes. The entire 12 human body state space will thus be transformed into multiple subspaces that are further dissected through 13 14 various dimensions. Specifically, the aim is to trace proteome-centric trajectories during major prenatal and postnatal stages, to profile longitudinal dynamic changes in complex proteomes during the development 15 and progression of representatives of complex diseases, and to determine the effects of non-genetic factors 16 17 (e.g., symbiotic microbiomes, lifestyles, and different environments) on the human proteome. These statecontextual proteomic data will be integrated with other human omics data from complementary efforts (e.g., 18 HuBMAP³⁵, Human Cell Atlas³⁶, Human Tumor Atlas Network³⁷, and the LifeTime Initiative³⁸) and 19 20 projected into a digitized model called Meta Homo Sapiens. Building such a model will be facilitated by 21 Composing Principles of the human body and it will be formulated using a 3D anatomical hierarchy that 22 records digital features of organs, tissues, body fluids and cells at each level and consist of time-sequential 23 frames, with each containing proteomic data measured and augmented within a unit period to represent the 24 human body state at a given timestamp.

25 3. Build the π -HuB Navigator The ultimate goal of the π -HuB project is to instantiate proteomics-driven phronesis medicine, which is a concept similar to the practical wisdom (Phrónesis) from ancient Greek that 26 27 is relevant to practical action in a particular situation. Unlike traditional and current paradigms of medicine, 28 phronesis medicine aims to develop the ability to provide temporally precise control of the human body state to prevent disease. This ability should include accurate, efficient monitoring, diagnosis and treatment 29 30 capabilities and highly robust decision-making capabilities for disease prediction, early warning, prevention, control, and health care. It will ultimately provide temporally precise control of the human body state to 31 32 prevent disease by establishing a medical model of popularization and normalization of monitoring, 33 diagnosis and treatment decisions and health management. Undertaken with a very keen eye toward

1 realizing this ultimate goal, we aim to develop the π -HuB navigator that will be a virtual state-space 2 instrument, created by the convergence of physiological phenotypes and proteomic-oriented spatial-3 temporal biochemical/biophysical information in cells, body fluids, tissues, and organs. It can transfer the prototype Meta Homo Sapiens model from primary body conditions to different secondary states to obtain 4 realistic models. This will be followed by creating a state space covering all key states of the human body 5 6 by simulating body dynamics with each model for specific periods, thereby tackling the most beneficial 7 approaches to prediction of outcomes based on non-invasive proteomic snapshots and longitudinal proteomic measurements. Ultimately, causal inference will be used to identify underlying triggers that 8 9 induce transitions between adjacent key states. Each state space can be regarded as a topological navigation 10 map where each node is the key state defined by the corresponding biomarkers and each edge between two nodes records the triggers to transform from one state to the other. Thus, building such a navigator will grant 11 12 an opportunity to track trajectories of wellness and health, to define factors important in disease risk assessment and early diagnosis, and to drive the development of novel therapeutic interventions and 13 14 intelligent healthcare approaches for redirecting unhealthy transitions to a long and prosperous life.

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16 Pillars for Building the π -HuB Navigator

17 To achieve the above goals, the project is being supported by six key pillars as follows (Fig. 2).

1. Human biospecimens Human biospecimens are the fundamental component of the π -HuB 18 project. To achieve the objectives outlined above, samples for π -HuB can be grouped into the following 19 20 categories. First, anatomy-based samples will consist of freshly prepared organs, tissues and live human 21 samples obtained with the highest ethical standards from post-mortem examinations. Second, twin cohorts will allow the calculation of the genetic component of observed variability in a population and benefit on 22 controlling confounding factors in etiological studies on complex diseases. Third, population-based cohorts 23 will be cross-sectional collections of high-quality biospecimens from a large number of individuals from 24 25 diverse geographical regions of the world with different lifestyles and subjected to different environments. 26 Finally, longitudinal cohort studies will apply non- or less-invasive approaches with relatively high 27 sampling frequency to sample healthy individuals or patients with defined exposures that have health or 28 therapeutic implications or outcomes.

In practice, the π -HuB project will first utilize samples from existing state-of-the-art biobanks around the world and is open to work closely with other resources being built. All samples in this project will be required to be well and consistently annotated with clinical and demographic information obtained from multiple sources, such as questionnaires, physical measurements, biochemical tests, medical imaging data, records of genetic variants implicated in disease susceptibility, and wearable device-based records, among others. Furthermore, annotations should be performed by using agreed metadata standards that are key for 1 data accessibility and interoperability and for artificial intelligence (AI)-based data integration across

2 bioinformatic resources³⁹.

3 2. Measurement technology innovations Considering that the project aims to profile the human proteome at unprecedented resolution and scale and that it has an intended time horizon of 30 years, the 4 advancement of measurement technologies is crucial to its success (Box 2). For example, there is a pressing 5 6 need to identify and measure minute amounts of proteins from single cells. In recent years, we have 7 witnessed tremendous progress in the development of MS-based single-cell proteomic (SCP) technologies⁴⁰. However, a real-world, large-scale application of existing technologies for profiling millions to billions of 8 9 human cells, is still very far from the state-of-the-art. Whereas current MS-based SCP technologies are able to measure up to \sim 4,500 proteins per single cell⁴¹, the limited sample throughput due to the lack of 10 multiplexing strategies remains a major shortcoming of SCP analyses. In this regard, the project will start 11 12 by profiling a cell type-resolved human proteome atlas (See below), while in parallel π -HuB will coordinate and support an international community effort to accelerate and benchmark MS-based SCP technologies 13 14 across different platforms and laboratories. Once we can achieve a relatively high analytical performance for SCP analysis in the π -HuB data collection centers (e.g., >3,000 proteins per cell at a throughput of 15 ~1,000 cells per day), the project will then launch the first initiative to collect SCP data from human samples. 16 17 Meanwhile, we will closely track novel concepts and technologies for single-molecule protein sequencing 18 that have substantial potential to enable broad sequence coverage in single-cell profiling⁴².

In addition, the π -HuB project will also develop, integrate and apply robust technologies for the generation of multidimensional proteomic data indicating the functional states of the proteome. These technologies are exemplified by PTMs, structural states, localization, and interactions and context-specific interdependencies of these attributes. To facilitate this, the π -HuB project will develop a specific technology scout division separate from its own technology hub, seeking to identify and fund emerging technologies.

24 As technologies will be rapidly evolving, data acquired in the early stage of this project may become superseded by data collected at a later stage. However, these early data will be invaluable for the 25 26 development and benchmarking of data analysis and integration tools, for providing training opportunities 27 for researchers in the field, for demonstrating data and sample interoperability procedures within the 28 consortium and for supporting pilot studies. Moreover, we reasoned that, like HGP, the project will also 29 proceed in stages where 'drafts' of the high-fidelity human proteome atlases will become available at 30 regular intervals, which will be further iterated to more accurate and complete versions by using newer 31 technologies.

32 3. Computational technology innovations Beyond data collection, our ambition also extends to developing
 33 methods and tools for data integration, analysis and interpretation (Box 2). Data-driven modeling
 34 approaches, such as automated machine learning (autoML), have proved powerful in approximating many

virtual and real-world systems⁴³. However, transforming a biological 'black box' into a digital system does 1 2 not typically provide us with any intellectual knowledge or insight that would enable it to be trusted for 3 clinical practice. Therefore, the π -HuB project will push the boundaries in biomedicine by unveiling the molecular re-construction of the human body. Inspired by success in mathematical intuition guidance and 4 5 hypothesis proposal⁴⁴, explainable artificial intelligence (XAI) methods, large language models (LLMs)⁴⁵, and other yet-to-be-conceived approaches will be exploited to interpret a fit-for-purpose deep learning 6 7 model of the human body with escalating resolutions, from molecular to cellular to organ and systems levels, enabling the discovery of knowledge about biological events and the establishment of construction 8 9 theories⁴⁶. In this context, it will be key to attract AI practitioners to the proteomics field. With this new knowledge, several 'white box' prototype *meta-Homo sapiens* models will be constructed to serve as the 10 critical preliminary conditions upon which π -HuB will build the foundation model of the system. We believe 11 that the π -HuB project is ideally positioned to meet the data science challenges because of the availability 12 of proteomic data sets acquired by the project consortium that are unique in terms of the size, consistency 13 14 of collection, annotation and processing and their coverage of multiple layers of the proteome.

4. Big-Science infrastructure Since very large numbers of human samples (e.g., sorted single cells from 15 human organs and biospecimens from clinical cohorts) will be analyzed in the π -HuB project, ultra-high 16 17 throughput facilities for data manufacturing, collection and processing will be required. Ideally, such 18 facilities require expertise and streamlined, reproducible pipelines to process human samples, profile 19 proteome-centric molecular data in samples, and store, transfer, process, and interpret those data. Therefore, 20 the π -HuB project will be establishing national facilities/centers as the Big Science infrastructure for the 21 collection and processing of multi-layer proteomic data. Minimally, during the first stage of the π -HuB 22 project, such an infrastructure should be able to process 1,000-2,000 samples per day (SPD) and generate 1TB of MS raw data per day (as of today, although this amount is expected to increase in parallel with the 23 developments in technology and instrumentation). In China, only a few existing programs possess such 24 25 analytical capacities including automation workstations for 'one-stop' sample preparation, more than 40 cutting-edge high-resolution mass spectrometers and a high-performance computing system called 'Tianhe-26 27 II²³. In addition, many other Big Science infrastructures and National Laboratories across China have pledged support for the π -HuB project, bringing state-of-the-art single cell technologies, multimode trans-28 29 scale biomedical imaging technologies and a cloud-based high-performance AI computing system to the 30 project. Furthermore, the π -HuB project is partnering with existing infrastructures from research entities attached to universities or other institutions worldwide, such as the Netherlands Proteomics Center and 31 32 ProCan in Australia.

5. *Open resources* The π -HuB project will emphasize highly efficient, international, open resources, including standards, samples and their annotations, data, and key analysis tools. Like other large community

1 resources with a broad utility, the project will require an open sharing framework to ensure transparent 2 global collaboration between researchers, funding agencies, and stakeholders. In this framework, π -HuB will maximize the importance of reusing collected human samples and reanalyzing already generated data 3 to maximize the benefits from scientific advances, while minimizing risks to participant privacy and 4 acknowledging the contributions of researchers. For example, all π -HuB-generated (non-sensitive) raw data 5 6 will be directly available to the international scientific community through several well-established data 7 portals implementing the FAIR (Findable, Accessible, Interoperable and Reusable) data principles, such as those established by the ProteomeXchange Consortium, including PRIDE and iProX^{47,48}. In addition, 8 9 bioinformatics infrastructure will be developed to integrate proteomics atlases into UniProt, the most 10 popular protein knowledgebase in the world, so that information is available to the whole life science community. Moreover, the project will enable clinicians and patients to freely inquire about medical 11 intervention strategies by developing a web-based 'Meta Homo sapiens' computational framework based 12 13 on π -HuB molecular and spatial data.

14 6. International research teams The sixth pillar is 'people', including researchers, software engineers, clinicians, pathologists, project managers, administrators, financial staff, lawyers, commercial 15 entities and so on. The implementation of the π -HuB project requires synergy between a plethora of people 16 globally to work collaboratively under the guidance of a decision-making body and clear governance and 17 18 accountability guidelines. Specifically, the π -HuB project will be steered and governed by an Executive 19 Committee and overseen an advisory board. In addition, capacity building and cultural interchange will 20 benefit international researchers in the exchange of ideas and results and also in research and intellectual 21 culture. To foster this, π -HuB will establish several scholarship or fellowship programs to promote these 22 exchanges, through which it will attract additional early career scientists to participate in this visionary 23 international project.

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25 Challenges

26 1. Ethics Within the framework of the π -HuB project, several measures are proposed to mitigate the identified ethical and regulatory challenges in proteomic research⁴⁹. Especially with regards to human 27 28 samples, it is essential for the project to establish a common, flexible and generally accepted framework 29 with respect to ethics approval criteria, patient/donor consent, sample annotation ontology material transfer 30 agreements (MTA) and non-disclosure agreements (NDA) that can be accepted by governments from different geographical regions. Additionally, the risk of re-identifying individuals through their proteomic 31 features demands meticulous assessment and management. To safeguard the ethical integrity and foster 32 societal acceptance of the π -HuB project, we will establish a specialized ethics committee whose primary 33 34 role will be to oversee every facet of the project, encompassing biospecimen collection, analysis, data

1 management, and information dissemination. Adopting this proactive stance towards ethical and regulatory

compliance will not only enhance the scientific credibility of the π-HuB project but also strengthen public
trust and participation.

2. Big Data π -HuB will work closely with existing international data centers such as the ProteomeX change 4 consortium for the sake of consistency of data standards and management rules widely adopted in the field 5 6 of proteomics. Nonetheless, a fit-for-purpose data center specifically designed for the π -HuB project is 7 needed. First, new upgrades will be required to store and manage more metadata (e.g., clinical information) 8 that can meet the data management requirements of the project. Second, it should support multi-omics and 9 multi-model data management and applications. Last but not least, it needs to be easily accessible for researchers worldwide. This will be achieved by the establishment of sub-centers in different countries that 10 can meet the legal constraints of each country⁵⁰, while meeting the requirements of the π -HuB project by 11 using data management system software and technical support from the headquarter center. 12

13 3. Data generation and integration The massive amount of data from different modalities will be collected 14 across the international teams. Thus, it is necessary to ensure that data generated across different teams are comparable and integrable. The π -HuB consortium will first ensure all human samples to be processed 15 using standard operating procedures (SOPs) with respect to collection, annotation, handling, storage, and 16 17 tracking. Additionally, to ensure that each data collection team can produce high-quality and unified proteome-centric datasets, the π -HuB project will adopt the HUPO Proteome Standards Initiative (PSI)⁵¹ 18 19 principles to standardize both state-of-the-art MS-based and non-MS-based approaches in terms of sample 20 preparation, methodological settings, data acquisition, processing and error control, and develop the SOPs 21 for each step. Given the anticipated rapidity of methodological development, the consortium will also 22 develop and share standards, test samples, and benchmarking data to help each research center update SOPs 23 for new techniques.

Furthermore, new computational methods and ML models with strong generalization ability⁵² are needed 24 to further develop proteomic data analysis (e.g., quality control⁵³, data cleansing, normalization⁵⁴, and 25 missing-value imputation) and specifically address questions that can benefit from multimodal and inter-26 27 center/laboratory measurement. As such, we will develop a centralized, cloud-based, interactive platform 28 for data sharing and analysis that will host standardized tools and pipelines for data processing, integration and interpretation. Lastly, the consortium will provide comprehensive training and support to all consortium 29 members to ensure familiarity and compliance with the SOPs and computational tools. These efforts will 30 develop approaches to support the mobilization of the π -HuB data, support the discovery of novel insights 31 by providing novel algorithms and develop novel models for unifying multiple-omics layers. 32 33 4. Modeling The π -HuB Navigator will build upon a computationally driven model (so called Meta Homo

34 Sapiens) of the human proteome, which is an extremely complex task. In our initial plan, this model will

consist of three basic modules (Fig. 3): 1) a state identifier to encode different states of the human body in the state space through proteome-centric measurements, followed by the integration of phenotypic information of the human body through a multi-modality LLM. 2) a lineage tracer to quantify the transition probability between each pair of states under different physiological/pathological/therapeutic conditions; for example, the transition probability between each pair of states can be estimated through Monte Carlo methods⁵⁵. 3) a path planner to search for the optimal treatment trajectory by balancing various objectives such as the efficacy against the financial costs and individual's compliance.

8 5. Democratizing proteomics Compared to genomics and its related sequencing technologies, the power of 9 proteomics is far from being fully appreciated by the public and, in fact many clinicians. Thus, building the interface of the π -HuB project to clinicians and the public is a major aim in addition to the research goals 10 of the project to gain public awareness and participation. Such advocacy is needed as a driving force in both 11 12 sample procurement and addressing the most impactful and pressing needs in disease focused research. The π -HuB consortium will also provide training and education of clinicians, pathologists, and patients to 13 14 interpret and use proteomics data, and push proteomics-driven discoveries to the clinics and health care. In particular, the tools hosted in this interface will assist researchers and clinicians in understanding the 15 biological pathways of specific state changes, guiding daily research and clinical practice. 16

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18 Major Outcomes of π -HuB Phase One

To enable π -HuB to be a broadly applicable project, it is necessary to maximize relevance to the community 19 20 by setting deliverables and expected outcomes as a series of staged programs undertaken in a relatively 21 short timeframe. During the initiation and development stage (2024-2033, herein referred to as 'phase one'), we will build an international cooperative network to lay the technical foundation of this project by 22 23 promoting methodological advances, benchmarking state-of-the-art technologies for standardization, building the computational infrastructures for data integration and modeling, and so on. Meanwhile, it is 24 25 also important for the project, in a relatively short-term frame, to achieve major outcomes as follows (Table 26 1).

27 1. Principles of cell type organization The π -HuB project will eventually support studies that generate 28 single cell resolution atlases of all major human organs and tissues from people who identify as emanating 29 from different ancestral populations/origin. However, during phase one, we will initially build reference cell-type proteome atlases for all major organs using a combination of state-of-the-art flow sorting⁵⁶ and 30 parallel MS acquisition platforms⁵⁷. Moreover, rapidly evolving spatial proteomics technologies will 31 provide additional insights into the secreted proteins in the surrounding microenvironment and subcellular 32 localization of the proteome at the tissue, cellular, and molecular levels. In this regard, multiple cutting-33 edge and synergistic approaches will be implemented, including MS-based, multiplex immuno-affinity-34

based and super-resolution imaging-based methods^{58,59}. Additionally, the emerging proximity labeling and *in vivo* crosslinking approaches will enable the profiling of protein subcellular localization, protein complexes and PPIs in diverse human cell types^{60,61}. These analyses will provide versatile opportunities to uncover new molecular/cellular mechanisms of biological processes in shaping diverse cell types and cell states within each organ. Together, we envision that the cell-type-resolved, multidimensional proteome atlases, in combination with cutting-edge computational and bioinformatic approaches, are able to uncover building principles of cell type organization of major tissues/organs.

2. Proteomics-driven lifestyle guidelines During phase one, we will focus on the most dominant factors 8 9 that shape/remodel the proteome of healthy individuals. Specifically, we will accumulate a large number of 10 biofluid proteomes from large-scale natural populations, aiming 1) to map quantitative trait loci for circulating/tissue proteins and protein allelic variants associated with genetic variants implicated in disease 11 12 susceptibility, allowing us to construct disease-causing pathways; 2) to trace the proteomic trajectory over the human lifespan by quantifying dynamic changes in the biofluid proteomes of five major prenatal cycles 13 14 (e.g., gametogenesis, fertilization, embryonic development, fetal development, and delivery) and five major postnatal cycles (e.g., adolescence, puberty, gestation, menopause and old age); 3) to analyze the effects of 15 four major dietary nutrition patterns (i.e., Western, Japanese, Mediterranean and subsistence)⁶² on the 16 human biofluid proteome; 4) to map the proteomes of populations in six major ecological environments 17 18 that are classified by the Köppen-Geiger map (e.g., hot, warm, cold, arid, polar and highland)⁶³, and analyze 19 the trajectory of the human biofluid proteome during acclimatization and adaptation; 5) to map interactions 20 of the human gut and skin proteome with representative microbiomes from internal and external 21 environments, and to construct the adaptation trajectory of the human proteome in response to microbiomes; 22 and 6) to map the responses of the human proteome to various clinical intervention strategies such as 23 medication, diet, and exercise. Together, these analyses will generate a resource of human proteome traits associated with the lifetime states as indicated above. Such a resource will provide opportunities to develop 24 25 a proteomic health score through a neural network or LLM, thereby shaping up proteomics-driven lifestyle 26 guidelines.

27 3. Generalization of PDPM In the past decade, there has been growing evidence that proteomic approaches 28 can facilitate the mechanistic understanding of diseases as well as facilitate biomarker discovery and optimize therapy development. In particular, proteomics alone has been able to identify potential 29 biomarkers or potential therapeutic targets for many tumor types^{32,64-67} and a variety of other diseases⁶⁸⁻⁷³. 30 Despite these advances, most proteomic findings in the context of human diseases have yet to be validated 31 and treatment suggestions arising from the data have yet to be approved. For example, most potential 32 biomarkers identified by proteomic studies are generated from small-scale, retrospective studies, lacking 33 34 the basis for the subsequent generalization of using such biomarkers in a wider population. The π -HuB

1 consortium that consists of multi-interdisciplinary researchers and clinicians provides an unprecedented 2 opportunity to reimagine biomarker discovery through a proteomic approach. We therefore reason that, 3 under the umbrella of π -HuB, it will be more feasible to organize large-scale, international, multicenter, cohort studies for validating new biomarkers for early and companion diagnosis of major diseases. As such, 4 we plan to map the proteomes of 10 major organs and corresponding biofluids at different 5 pathophysiological stages, focusing on 3-5 representative diseases for each related organ. Such analyses, 6 7 together with the aforementioned tissue proteome atlases with cell type resolution and biofluid proteome atlases with life-oriented adaptive proteome atlases, will allow the construction of proteomic evolutionary 8 9 trajectories mapping the occurrence and development of these diseases and the pathways associated with 10 specific life stages and survival conditions. Furthermore, the π -HuB project will actively collaborate with clinicians, policymakers, and industrial partners to catalyze the discovery of new protein-based biomarkers 11 12 and drug targets that can be applied in clinics to diagnose disease and drug development, driving a paradigm shift to proteomics-driven precision medicine. 13

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15 Outlook

16 Since its inception in 2020, the π -HuB consortium has grown to be an international collaborative force of more than 100 members mobilizing scientists worldwide across academic, industrial and government 17 18 sectors in the protein and health sciences. The π -HuB project will likely foster further global collaboration and discussion by integrating the results of a worldwide community of multidisciplinary scientists to better 19 20 understand human biology and to advance medicine from disease trajectory predictions to new treatment 21 options. We anticipate that the π -HuB project will make a major contribution to biomedical research in the coming decades, facilitating disease prevention and diagnosis, accelerating drug discovery and ultimately 22 23 ushering in an era of proteomics-driven phronesis medicine.

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1 Box 1. Complexities of The Human Proteome

2 First, for a human being at any time, there is immense molecular diversity of the proteins in the human 3 proteome at multiple scales, including their level of expression and degradation, their functional state 4 indicated by post-translational modifications (PTMs), protein-protein interactions (PPIs) and shapes and 5 their cellular and subcellular location. Collectively the proteins and their attributes shape the approximately 6 37 trillion cells in the human body with a wide range of morphology and function. Second, for any human 7 society, the genomic diversity of the human population leads to a larger diversity of proteomes in the population, as each person will have a special private proteome and therefore a special private functional 8 9 state. Third, during human lifetime, an individual's proteome is highly dynamic and can be affected by 10 disparate external and internal factors, such as somatic mutations, the human microbiome (which can be 11 defined as the microbial ecosystems that reside in various habitats of the body, for example, the human gut), the type of lifestyle (e.g., diet, food, nutritional supplements, physical activity and drugs), the occurrence 12 of somatic mutations and the state of the external environment, all of which are intimately related to human 13 14 health and diseases.

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16 Box 2. Key Technologies for the π -HuB Project

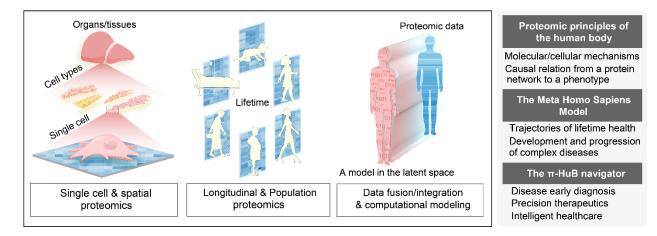
- Single Cell Proteomics: π-HuB will fully benchmark state-of-the-art SCP methods (e.g., nanoPOTS⁷⁴, SCoPE-MS⁷⁵, and scPiMS⁷⁶) and determine the right time to launch the first large-scale initiative to collect SCP data from human samples. In order to further increase the throughput of SCP analysis, it is also important to urge engineering-level innovations for fully integrated/automated ng-level sample preparation technologies⁷⁷ and single-molecule protein sequencing technologies⁷⁸.
- Spatial Proteomics: π-HuB will initially apply the Deep Visual Proteomics (DVP) technology⁷⁹ or its derivatives to spatially profile proteomes across different cell types. Nonetheless, new concepts and technologies for spatial proteomics are warranted by integrating AI-based tissue imaging navigation, high-throughput and pixel-format sampling, multimodal data acquisition and integration³⁴.
- Plasma Proteome Profiling: π-HuB will apply MS-based or affinity-based technologies for plasma proteome profiling, which have been demonstrated to simultaneously analyze thousands of proteins in many thousands of plasma samples with high throughput^{80,81}.
- Functional Proteomics: π-HuB will focus on new chemical biological and biophysical approaches
 for targeting and enriching native functional states of the human proteome. For example, recent
 technological advances have enabled the direct detection of subcellular localization, dynamic changes,
 and interactions of proteins *in vivo*^{60,61,82,83}.
- Automated Machine Learning: π-HuB aims to automate the end-to-end process of applying machine
 learning to analyze and interpret large-scale proteomics data^{84,85}, which involves tailoring the selection
 and optimization of machine learning models, facilitating non-expert access to complex multi-modal
 data analysis, and addressing challenges on the proteomics study such as protein identification,
 quantification, and biomarker discovery, early disease diagnosis, optimal therapeutic interventions,
 and dynamics of biological processes.
- **Explainable Artificial Intelligence:** π -HuB will develop XAI methods that provide clear and understandable explanations of their findings in proteomics analysis⁸⁶, which, in particular, can validate AI-driven hypotheses in proteomics, ensuring that AI conclusions are scientifically sound and interpretable, enhances trust and collaboration between computational scientists and experimental biologists by providing transparent decision-making processes. Furthermore, XAI can bridge the gap between AI models and practical applications (e.g., predictions of disease risk at the individual level and the effect of drugs or drug combinations on the state of cells).
- Large Language Model: π-HuB will build advanced AI models trained on extensive biomedical literature to understand and generate language specific to the proteomics field⁴⁵, which are expected to analyze and synthesize vast amounts of biomedical text, extract insights from unstructured data sources such as research papers relevant to proteomics, and assist in identifying patterns, potential therapeutic targets, and novel connections within the complex human proteomics data.
- 51

1 Figure legends

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Figure 1. Overall goals of the π **-HuB project.** The schematic depicts the development and integration of major technological strategies for achieving the scientific milestones for each goal. The π -HuB project will start with the extensive measurement of human samples and the generation of data across digital proteomic anatomy spaces and individuals' state spaces in lifetime. Then, it will take the advantages of latest advances in data and computational sciences to uncover composing principles of the human body, to generate a

- 8 digitized model called *Meta Homo Sapiens*, and to build a 'GPS' (Global Positioning System) for the human
- 9 body and body's states.
- 10



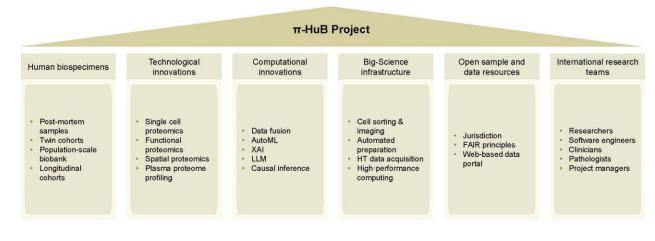
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Figure 2. Key pillars for implementing the π -HuB project. To achieve the π -HuB project goals, the project is being supported by six pillars, of which key components are listed. autoML: Automated

16 machine learning, XAI: Explainable artificial intelligence, LLM: large language model, HT: high-

17 throughput, FAIR: Findable, Accessible, Interoperable and Reusable.

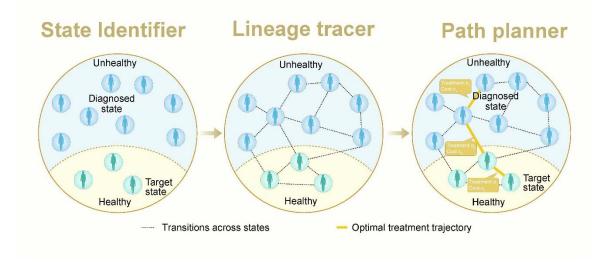
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Figure 3. The basic modules of the π -HuB navigator. A state identifier generates key states of human body based on massive hierarchical measurements from large cohorts. It is followed by a dynamic modelbased lineage tracer to detect possible transitions between states under all available treatments. Given the

- 1 established state space, a path planner can search for a treatment trajectory while considering various
- 2 objectives and constraints.



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Table

Table 1. Major outcomes of π-HuB Phase One

Expected Outcomes	Principles of cell type- based tissue organization	Proteomics-driven lifestyle guidelines	Proteomics-driven precision medicine
Biospecimen inputs	All major organs from post- mortem of healthy donors	Biobanks of natural populaiton	Large-scale international multicenter patient cohorts
Key measurements	Proteinexpression,subcellularlocalization,PTMs and PPIs in each celltype	Protein expression and PTMs in body fluids or other non-invasive human samples	Protein expression, PTMs, and PPIs indisease tissues and/or body fluids
Major deliverables	 A cell-type-resolved, multidimensional human proteome atlas New molecular/cellular mechanisms of biological processes 	 A resource of human proteome traits associated with lifetime states A proteomic health score 	 A resource of human proteome traits associated with major diseases New biomarkers and therapeutic targets

1	References		
2	1	Venter, J. C. <i>et al.</i> The sequence of the human genome. <i>Science</i> 291 , 1304-1351 (2001).	
3	2	Lander, E. S. <i>et al.</i> Initial sequencing and analysis of the human genome. <i>Nature</i> 409 , 860-921 (2001).	
4	3	Aebersold, R. & Mann, M. Mass-spectrometric exploration of proteome structure and function. <i>Nature</i> 537 ,	
5		347-355 (2016).	
6	4	Abbott, A. And now for the proteome. <i>Nature</i> 409 , 747 (2001).	
7	5	Fields, S. Proteomics. Proteomics in genomeland. Science 291, 1221-1224 (2001).	
8	6	The proteome isn't genome II. Nature 410, 725 (2001).	
9	7	Adhikari, S. et al. A high-stringency blueprint of the human proteome. Nat Commun 11, 5301 (2020).	
10	8	Omenn, G. S. et al. The 2022 Report on the Human Proteome from the HUPO Human Proteome Project. J	
11		Proteome Res 22, 1024-1042 (2023).	
12	9	Kusebauch, U. et al. Human SRMAtlas: A Resource of Targeted Assays to Quantify the Complete Human	
13		Proteome. Cell 166, 766-778 (2016).	
14	10	Cyranoski, D. China takes centre stage for liver proteome. Nature 425, 441 (2003).	
15	11	Jia, H. & Louet, S. China pushes liver proteomics. Nat Biotechnol 22, 136 (2004).	
16	12	He, F. Human liver proteome project: plan, progress, and perspectives. Mol Cell Proteomics 4, 1841-1848	
17		(2005).	
18	13	Wang, J. et al. Toward an understanding of the protein interaction network of the human liver. Mol Syst Biol	
19	15	13 , 965 (2017).	
20	14	Wang, Q. <i>et al.</i> Acetylation of metabolic enzymes coordinates carbon source utilization and metabolic flux.	
20	14	Science 327 , 1004-1007 (2010).	
22	15		
	15	Zhao, S. <i>et al.</i> Regulation of cellular metabolism by protein lysine acetylation. <i>Science</i> 327 , 1000-1004	
23	16	(2010).	
24	16	Sharma, K. et al. Cell type- and brain region-resolved mouse brain proteome. Nat Neurosci 18, 1819-1831	
25		(2015).	
26	17	Doll, S. et al. Region and cell-type resolved quantitative proteomic map of the human heart. Nat Commun 8,	
27		1469 (2017).	
28	18	Ni, X. et al. A region-resolved mucosa proteome of the human stomach. Nat Commun 10, 39 (2019).	
29	19	Dyring-Andersen, B. et al. Spatially and cell-type resolved quantitative proteomic atlas of healthy human	
30		skin. Nat Commun 11, 5587 (2020).	
31	20	Rieckmann, J. C. et al. Social network architecture of human immune cells unveiled by quantitative	
32		proteomics. Nat Immunol 18, 583-593 (2017).	
33	21	Wilhelm, M. et al. Mass-spectrometry-based draft of the human proteome. Nature 509, 582-587 (2014). This	
34		paper, together with Ref22, that has revealed the initial version of the tissue/organ-centric human	
35		proteome by applying mass spectrometry-based approaches.	
36	22	Kim, M. S. et al. A draft map of the human proteome. Nature 509, 575-581 (2014).	
37	23	Cyranoski, D. China pushes for the proteome. <i>Nature</i> 467 , 380 (2010).	
38	24	Rodriguez, H., Zenklusen, J. C., Staudt, L. M., Doroshow, J. H. & Lowy, D. R. The next horizon in precision	
39		oncology: Proteogenomics to inform cancer diagnosis and treatment. <i>Cell</i> 184 , 1661-1670 (2021).	
40	25	Irmisch, A. <i>et al.</i> The Tumor Profiler Study: integrated, multi-omic, functional tumor profiling for clinical	
41	23	decision support. <i>Cancer Cell</i> 39 , 288-293 (2021).	
42	26	Uhlén M et al., A human protein atlas for normal and cancer tissues based on antibody proteomics. <i>Mol</i>	
43	20	<i>Cell Proteomics.</i> 4, 1920-1932 (2005).	
43 44	27	Uhlén M et al., Tissue-based map of the human proteome. Science 347 , 1260419 (2015).	
	27		
45	28	Tully, B. <i>et al.</i> Addressing the Challenges of High-Throughput Cancer Tissue Proteomics for Clinical	
46	•	Application: ProCan. Proteomics 19, e1900109 (2019).	
47	29	Eldjarn, G. H. et al. Large-scale plasma proteomics comparisons through genetics and disease associations.	
48		<i>Nature</i> 622 , 348-358 (2023).	
49	30	Xu, Y. et al. An atlas of genetic scores to predict multi-omic traits. Nature 616, 123-131 (2023).	
50	31	Sun, B. B. et al. Genomic atlas of the human plasma proteome. Nature 558, 73-79 (2018).	
51	32	Jiang, Y. et al. Proteomics identifies new therapeutic targets of early-stage hepatocellular carcinoma. Nature	
52		567, 257-261 (2019). The first study that has showcased the concept of proteomics-driven precision	
53		medicine.	
54	33	Kelly, R. T. Single-cell Proteomics: Progress and Prospects. Mol Cell Proteomics 19, 1739-1748 (2020).	
55	34	Mund, A., Brunner, A. D. & Mann, M. Unbiased spatial proteomics with single-cell resolution in tissues. Mol	

55 34 Mund, A., Brunner, A. D. & Mann, M. Unbiased spatial proteomics with single-cell resolution in tissues. *Mol*

1		Cell 82, 2335-2349 (2022). A review that has summarized state-of-the-art spatial proteomics for human
2		samples.
3	35	Hu, B. C. The human body at cellular resolution: the NIH Human Biomolecular Atlas Program. <i>Nature</i> 574,
4		187-192 (2019).
5	36	Elmentaite, R., Dominguez Conde, C., Yang, L. & Teichmann, S. A. Single-cell atlases: shared and tissue-
6		specific cell types across human organs. Nat Rev Genet 23, 395-410 (2022).
7	37	Rozenblatt-Rosen, O. <i>et al.</i> The Human Tumor Atlas Network: Charting Tumor Transitions across Space and
8	51	Time at Single-Cell Resolution. Cell 181, 236-249 (2020).
9	38	Rajewsky, N. <i>et al.</i> LifeTime and improving European healthcare through cell-based interceptive medicine.
10	50	Nature 587, 377-386 (2020).
10	39	Mann, M., Kumar, C., Zeng, W. F. & Strauss, M. T. Artificial intelligence for proteomics and biomarker
12	39	discovery. Cell Syst 12, 759-770 (2021).
12	40	
	40	Perkel, J. M. Single-cell proteomics takes centre stage. <i>Nature</i> 597 , 580-582 (2021).
14	41	Guzman, U. H. <i>et al.</i> Ultra-fast label-free quantification and comprehensive proteome coverage with narrow-
15	10	window data-independent acquisition. Nat Biotechnol (2024).
16	42	MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods.
17		Nat Methods 20, 339-346 (2023). A review that has summarized the next-generation proteomics
18		technologies.
19	43	Bi, K. et al. Accurate medium-range global weather forecasting with 3D neural networks. Nature 619, 533-
20		538 (2023).
21	44	Davies, A. et al. Advancing mathematics by guiding human intuition with AI. Nature 600, 70-74 (2021).
22	45	Thirunavukarasu, A. J. et al. Large language models in medicine. Nat Med 29, 1930-1940 (2023).
23	46	Kang, M., Ko, E. & Mersha, T. B. A roadmap for multi-omics data integration using deep learning. Brief
24		<i>Bioinform</i> 23 (2022).
25	47	Chen, T. et al. iProX in 2021: connecting proteomics data sharing with big data. Nucleic Acids Res 50, D1522-
26		D1527 (2022).
27	48	Deutsch, E. W. et al. The ProteomeXchange consortium at 10 years: 2023 update. Nucleic Acids Res 51,
28		D1539-D1548 (2023).
29	49	Fierro-Monti, I., Wright, J. C., Choudhary, J. S. & Vizcaino, J. A. Identifying individuals using proteomics:
30		are we there yet? Front Mol Biosci 9, 1062031 (2022).
31	50	Bandeira, N., Deutsch, E. W., Kohlbacher, O., Martens, L. & Vizcaino, J. A. Data Management of Sensitive
32		Human Proteomics Data: Current Practices, Recommendations, and Perspectives for the Future. <i>Mol Cell</i>
33		Proteomics 20, 100071 (2021).
34	51	Deutsch, E. W. <i>et al.</i> Proteomics Standards Initiative at Twenty Years: Current Activities and Future Work. J
35	51	Proteome Res 22, 287-301 (2023). A perspective paper that has summarized the 20-year long community
36		effort for the proteomics community with respects to data formats, quality control and annoation.
37	52	Sharifi-Noghabi, H., Harjandi, P. A., Zolotareva, O., Collins, C. C. & Ester, M. Out-of-distribution
38	52	generalization from labelled and unlabelled gene expression data for drug response prediction. <i>Nature</i>
39		Machine Intelligence 3, 962-972 (2021).
	53	
40	55	Olivella, R. <i>et al.</i> QCloud2: An Improved Cloud-based Quality-Control System for Mass-Spectrometry-
41	51	based Proteomics Laboratories. <i>J Proteome Res</i> 20 , 2010-2013 (2021).
42	54	Chawade, A., Alexandersson, E. & Levander, F. Normalyzer: a tool for rapid evaluation of normalization
43		methods for omics data sets. J Proteome Res 13, 3114-3120 (2014).
44	55	James, F. Monte Carlo theory and practice. <i>Reports on Progress in Physics</i> 43 (1980).
45	56	Shapiro, E., Biezuner, T. & Linnarsson, S. Single-cell sequencing-based technologies will revolutionize
46		whole-organism science. Nat Rev Genet 14, 618-630 (2013).
47	57	Goncalves, E. et al. Pan-cancer proteomic map of 949 human cell lines. Cancer Cell 40, 835-849 e838 (2022).
48	58	Qiao, C. et al. Evaluation and development of deep neural networks for image super-resolution in optical
49		microscopy. Nat Methods 18, 194-202 (2021).
50	59	Qiao, C. et al. Rationalized deep learning super-resolution microscopy for sustained live imaging of rapid
51		subcellular processes. Nat Biotechnol 41, 367-377 (2023).
52	60	Liu, Z. et al. Bioorthogonal photocatalytic proximity labeling in primary living samples. Nat Commun 15,
53		2712 (2024).
54	61	Zhang, Z. et al. Progress, Challenges and Opportunities of NMR and XL-MS for Cellular Structural Biology.
55		<i>JACS Au</i> 4 , 369-383 (2024).
56	62	Scarmeas, N., Anastasiou, C. A. & Yannakoulia, M. Nutrition and prevention of cognitive impairment. Lancet

 classification updated. <i>Meteorologische Zeitschrift</i> 15, 259-263 (2006). Harel, M. <i>et al.</i> Proteomics of Melanoma Response to Immunotherapy Reveals Mitochondrial Dependence <i>Cell</i> 179, 236-250 e218 (2019). Xu, J. Y. <i>et al.</i> Integrative Proteomic Characterization of Human Lung Adenocarcinoma. <i>Cell</i> 182, 245-261 e217 (2020). Shi, Y. <i>et al.</i> Integrating LIF-mediated paracrine interaction for pancreatic cancer therapy and monitoring <i>Nature</i> 569, 131-135 (2019). Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsies. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1285 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheiner's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling of 10-100 mamualian cells. <i>Nat Commu</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Sun, <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana Chem</i>		<i>Neurol</i> 17 , 1006-1015 (2018).
 Harel, M. <i>et al.</i> Proteomics of Mclanoma Response to Immunotherapy Reveals Mitochondrial Dependence <i>Cell</i> 179, 236-250 e218 (2019). Xu, J. Y. <i>et al.</i> Integrative Proteomic Characterization of Human Lung Adenocarcinoma. <i>Cell</i> 182, 245-261 e217 (2020). Shi, Y. <i>et al.</i> Targeting LIF-mediated paracrine interaction for pancreatic cancer therapy and monitoring <i>Nature</i> 569, 131-135 (2019). Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsise. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. <i>et al.</i> Noninvasive proteome brofiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wirger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. <i>Nat Med</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nandoroplet processing platform for deep and quantitative proteome profiling of 10-10 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Preteiski, A. A. <i>et al.</i> Multi-generated single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteomers. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteome Profiling to Assess Human Health and Disease. <i>Cell</i>	63	Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. World Map of the Köppen-Geiger climate
 Cell 179, 236-250 e218 (2019). Xu, J. Y. et al. Integrative Proteomic Characterization of Human Lung Adenocarcinoma. Cell 182, 245-261 e217 (2020). Shi, Y. et al. Targeting LIF-mediated paracrine interaction for pancreatic cancer therapy and monitoring Nature 569, 131-135 (2019). Eckert, M. A. et al. Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. Nature 569, 733-732 (2019). Shen, B. et al. Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. Cell 182, 59-72 e15 (2020). Nie, X. et al. Multi-organ proteomic landscape of COVID-19 autopsies. Cell 184, 775-791 e714 (2021). Niu, L. et al. Nonirvasive proteomic biomarkers for alcohol-related liver disease. Nat Med 28, 1277-1287 (2022). Virreira Winter, S. et al. Urinary proteome profiling for stratifying patients with familial Parkinson's disease EMBO Mol Med 13, e13257 (2021). Wigger, L. et al. Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous betr cell trajectories towards type 2 diabetes. Nat Meda 3, 1017-1031 (2021). Johnson, E. C. B. et al. Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. Nat Neurosci 25, 213-225 (2022). Zhu, Y. et al. Single-cale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes for toorom: J. Proteom Res 24, 1883-1893(2024). Su, et al. Single call Integrated Spintip-Based Technology Applied for Deep Proteome Profiling of 10-100 mammalian cells. Nat Commun 9, 882 (2018). Petelski, A. A. et al. Multiplexed Spintip-Based Technology Applied for Deep Proteome Profiling. Ana Chem 88, 4864-4871 (2016). MacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods Nat Methods 20, 339-346 (2023)		
 Xu, J. Y. <i>et al.</i> Integrative Proteomic Characterization of Human Lung Adenocarcinoma. <i>Cell</i> 182, 245-261 e217 (2020). Shi, Y. <i>et al.</i> Targeting LIF-mediated paracrine interaction for pancreatic cancer therapy and monitoring <i>Nature</i> 569, 131-135 (2019). Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. <i>Nature</i> 569, 123-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic loimarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 107-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Multi-organ ptoteomers. <i>J Proteom Res</i> 24, 1883-1893 (2024). Chem, W. <i>et al.</i> Simple call Integrated Spinitp-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 30, 39-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5262 (2021). Buljan, M. <i>et al.</i> Acomputational framework for the inference of pro	64	· · · · · ·
 e217 (2020). Shi, Y. <i>et al.</i> Targeting LIF-mediated paracrine interaction for panereatic cancer therapy and monitoring <i>Nature</i> 509, 131-135 (2019). Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibrobasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nic, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsics. <i>Cell</i> 184, 775-791 e714 (2021). Nin, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun 9</i>, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Simple and Integrated Spinitp-Based Technology Applied for Deep Proteome Profiling. <i>Ana Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 (121)-1240 (2022).		
 Shi, Y. <i>et al.</i> Targeting LIF-mediated paracrine interaction for pancreatic cancer therapy and monitoring <i>Nature</i> 569, 131-135 (2019). Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsies. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling. <i>Ana Chem</i> 88, 4864-4871 (2016). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893 (2024). Chem, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Closal, in situ analysis of the structural proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016).	65	
 Nature 509, 131-135 (2019). Eckert, M. A. et al. Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. Nature 509, 723-728 (2019). Shen, B. et al. Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. Cell 182, 59-72 e15 (2020). Nie, X. et al. Nulti-organ proteomic landscape of COVID-19 autopsies. Cell 184, 775-791 e714 (2021). Niu, L. et al. Noninvasive proteomic biomarkers for alcohol-related liver disease. Nat Med 28, 1277-1285 (2022). Virreira Winter, S. et al. Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. et al. Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. Nat Metab 3, 1017-1031 (2021). Johnson, E. C. B. et al. Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. Nat Neurosci 25, 213-225 (2022). Zhu, Y. et al. Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mamalian cells. Nat Commun 9, 882 (2018). Petelski, A. A. et al. Multiplexed single-cell proteomics using SCOPE2. Nat Protoc 16, 5398-5425 (2021). Su. et al. Simple Cell Analysis of Proteoforms. J Proteome Res 24, 1883-1893(2024). Chen, W. et al. Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. Ana. Chem 88, 4484-4871 (2016). MacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods Nat Methods 20, 339-346 (2023). Mund, A. et al. Deep Visual Proteomics defines single-cell identity and heterogeneity. Nat Biotechnol 40 1231-1240 (2022). Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. Cell Syst 2, 185-195		
 Eckert, M. A. <i>et al.</i> Proteomics reveals NNMT as a master metabolic regulator of cancer-associated fibroblasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsics. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Wirreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wirger, L. <i>et al.</i> Multi-ornics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Multipedet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multipeded sigle-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Bampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> Acomputational framework for the inference of protein complex remo	66	
 fibroblasts. <i>Nature</i> 569, 723-728 (2019). Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nie, X. <i>et al.</i> Multi-organ proteomic landscape of COVID-19 autopsies. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related charges not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCOPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single call Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Pasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-192 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Mud, A. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Pla		
 Shen, B. <i>et al.</i> Proteomic and Metabolomic Characterization of COVID-19 Patient Sera. <i>Cell</i> 182, 59-72 e15 (2020). Nic, X. <i>et al.</i> Multi-organ proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wirger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 30, 393-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> Advances and Utility of the Human Plasma Proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Buijan, M. <i>et al.</i>	67	e
 (2020). Nic, X. et al. Multi-organ proteomic landscape of COVID-19 autopsies. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. et al. Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. et al. Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. et al. Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. et al. Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. et al. Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. et al. Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. et al. Simple and Integrated Spinitp-Based Technology Applied for Deep Proteome Profiling. <i>Ana Chem</i> 88, 4864-4871 (2016). MaacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. et al. Deep Visual Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. et al. Just Add Data: automate methine learning framework for disease classification. <i>Bioinformatici</i> 38, 3415-3421 (2022). Ts		
 Nie, X. et al. Multi-organ proteomic landscape of COVID-19 autopsies. <i>Cell</i> 184, 775-791 e714 (2021). Niu, L. et al. Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1287 (2022). Virreira Winter, S. et al. Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. et al. Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous bett cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. et al. Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. et al. Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. et al. Multipreed single-cell proteomics using SCOPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. et al. Simple Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. et al. Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MaacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Muund, A. et al. Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Methods</i> 20, 152-1529 (2016). Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. et al. A computational framework for the inference of protein complex remodeling from whole-proteome measuremen	68	
 Niu, L. <i>et al.</i> Noninvasive proteomic biomarkers for alcohol-related liver disease. <i>Nat Med</i> 28, 1277-1285 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteome forms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022).<td>60</td><td></td>	60	
 (2022). Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, F. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I		
 Virreira Winter, S. <i>et al.</i> Urinary proteome profiling for stratifying patients with familial Parkinson's disease <i>EMBO Mol Med</i> 13, e13257 (2021). Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-106 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteomic by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, N. <i>et al.</i> Autodolal, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (202	70	•
 <i>EMBO Mol Med</i> 13, e13257 (2021). <i>Construction of the intervention of the interventing from </i>	71	
 Wigger, L. <i>et al.</i> Multi-omics profiling of living human pancreatic islet donors reveals heterogeneous beta cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCOPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Deutsch, E. W. <i>et al.</i> Advances and Utility of the situration proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Buljan, M. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Natu</i>	71	
 cell trajectories towards type 2 diabetes. <i>Nat Metab</i> 3, 1017-1031 (2021). Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	70	
 Johnson, E. C. B. <i>et al.</i> Large-scale deep multi-layer analysis of Alzheimer's disease brain reveals strong proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> Advances and Utility of the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). Elimarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	12	
 proteomic disease-related changes not observed at the RNA level. <i>Nat Neurosci</i> 25, 213-225 (2022). Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. <i>J. et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	72	
 Zhu, Y. <i>et al.</i> Nanodroplet processing platform for deep and quantitative proteome profiling of 10-100 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	13	
 mammalian cells. <i>Nat Commun</i> 9, 882 (2018). Petelski, A. A. et al. Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. et al. Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. et al. Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. et al. Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. et al. A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. et al. Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. et al. AutoDC: an automatic machine learning framework for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	71	
 Petelski, A. A. <i>et al.</i> Multiplexed single-cell proteomics using SCoPE2. <i>Nat Protoc</i> 16, 5398-5425 (2021). Su, P. <i>et al.</i> Single Cell Analysis of Proteoforms. <i>J Proteome Res</i> 24, 1883-1893(2024). Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> Acomputational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	/4	
 Su, P. et al. Single Cell Analysis of Proteoforms. J Proteome Res 24, 1883-1893(2024). Chen, W. et al. Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. Ana. Chem 88, 4864-4871 (2016). MacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods Nat Methods 20, 339-346 (2023). Mund, A. et al. Deep Visual Proteomics defines single-cell identity and heterogeneity. Nat Biotechnol 40 1231-1240 (2022). Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. Cell Syst 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. J Proteome Res 20, 5241-5263 (2021). Buljan, M. et al. Computational framework for the inference of protein complex remodeling from whole-proteome measurements. Nat Methods 20, 1523-1529 (2023). Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. Nat Struct Mol Biol 29, 978-989 (2022). Bai, Y. et al. AutoDC: an automatic machine learning framework for disease classification. Bioinformatics 38, 3415-3421 (2022). Elmarakeby, H. A. et al. Biologically informed deep neural network for prostate cancer discovery. Nature 598, 348-352 (2021). 	75	
 Chen, W. <i>et al.</i> Simple and Integrated Spintip-Based Technology Applied for Deep Proteome Profiling. <i>Ana. Chem</i> 88, 4864-4871 (2016). MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 		
 Chem 88, 4864-4871 (2016). MacCoss, M. J. et al. Sampling the proteome by emerging single-molecule and mass spectrometry methods Nat Methods 20, 339-346 (2023). Mund, A. et al. Deep Visual Proteomics defines single-cell identity and heterogeneity. Nat Biotechnol 40 1231-1240 (2022). Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. Cell Syst 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. J Proteome Res 20, 5241-5263 (2021). Buljan, M. et al. A computational framework for the inference of protein complex remodeling from whole-proteome measurements. Nat Methods 20, 1523-1529 (2023). Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. Nat Struct Mol Biol 29, 978-989 (2022). Tsamardinos, I. et al. Just Add Data: automated predictive modeling for knowledge discovery and feature selection. NPJ Precis Oncol 6, 38 (2022). Bai, Y. et al. AutoDC: an automatic machine learning framework for disease classification. Bioinformatics 38, 3415-3421 (2022). Elmarakeby, H. A. et al. Biologically informed deep neural network for prostate cancer discovery. Nature 598, 348-352 (2021). 		
 MacCoss, M. J. <i>et al.</i> Sampling the proteome by emerging single-molecule and mass spectrometry methods <i>Nat Methods</i> 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	, ,	
 Nat Methods 20, 339-346 (2023). Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	78	
 Mund, A. <i>et al.</i> Deep Visual Proteomics defines single-cell identity and heterogeneity. <i>Nat Biotechnol</i> 40 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 	10	
 1231-1240 (2022). Geyer, P. E. <i>et al.</i> Plasma Proteome Profiling to Assess Human Health and Disease. <i>Cell Syst</i> 2, 185-195 (2016). Deutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 	79	
 Geyer, P. E. et al. Plasma Proteome Profiling to Assess Human Health and Disease. Cell Syst 2, 185-195 (2016). Deutsch, E. W. et al. Advances and Utility of the Human Plasma Proteome. J Proteome Res 20, 5241-5263 (2021). Buljan, M. et al. A computational framework for the inference of protein complex remodeling from whole-proteome measurements. Nat Methods 20, 1523-1529 (2023). Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. Nat Struct Mol Biol 29, 978-989 (2022). Tsamardinos, I. et al. Just Add Data: automated predictive modeling for knowledge discovery and feature selection. NPJ Precis Oncol 6, 38 (2022). Bai, Y. et al. AutoDC: an automatic machine learning framework for disease classification. Bioinformatics 38, 3415-3421 (2022). Elmarakeby, H. A. et al. Biologically informed deep neural network for prostate cancer discovery. Nature 598, 348-352 (2021). 	, ,	
 (2016). Beutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	80	
 Beutsch, E. W. <i>et al.</i> Advances and Utility of the Human Plasma Proteome. <i>J Proteome Res</i> 20, 5241-5263 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 		
 (2021). Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 	81	
 Buljan, M. <i>et al.</i> A computational framework for the inference of protein complex remodeling from whole-proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	-	
 proteome measurements. <i>Nat Methods</i> 20, 1523-1529 (2023). Mackmull, M. T. <i>et al.</i> Global, in situ analysis of the structural proteome in individuals with Parkinson's disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). 	82	
 disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). 84 Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). 85 Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). 86 Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 		
 disease to identify a new class of biomarker. <i>Nat Struct Mol Biol</i> 29, 978-989 (2022). 84 Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). 85 Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). 86 Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 	83	Mackmull, M. T. et al. Global, in situ analysis of the structural proteome in individuals with Parkinson's
 84 Tsamardinos, I. <i>et al.</i> Just Add Data: automated predictive modeling for knowledge discovery and feature selection. <i>NPJ Precis Oncol</i> 6, 38 (2022). 85 Bai, Y. <i>et al.</i> AutoDC: an automatic machine learning framework for disease classification. <i>Bioinformatics</i> 38, 3415-3421 (2022). 86 Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 		disease to identify a new class of biomarker. Nat Struct Mol Biol 29, 978-989 (2022).
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 Elmarakeby, H. A. <i>et al.</i> Biologically informed deep neural network for prostate cancer discovery. <i>Nature</i> 598, 348-352 (2021). ¹State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ²International Academy of Phronesis 	85	Bai, Y. et al. AutoDC: an automatic machine learning framework for disease classification. Bioinformatics
598, 348-352 (2021). ¹ State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ² International Academy of Phronesis		38 , 3415-3421 (2022).
¹ State Key Laboratory of Medical Proteomics, Beijing Proteome Research Center, National Center for Protein Sciences (Beijing), Beijing Institute of Lifeomics, Beijing 102206, China. ² International Academy of Phronesis	86	Elmarakeby, H. A. et al. Biologically informed deep neural network for prostate cancer discovery. Nature
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