Title: Ionizable networks mediate pH-dependent allostery in SH2 signaling proteins

One-sentence summary: This paper investigates the role of pH in the allosteric regulation of signaling proteins with SH2 domains, specifically focusing on SHP2 and Src

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Abstract

Intracellular pH dynamics regulate normal cell biology, but most molecular drivers

remain unknown. We developed a computational pipeline to identify pH-sensitive proteins and

their mechanisms. We applied the pipeline to SHP2, a pH-sensitive signaling protein, with

unknown mechanism. We found that SHP2 phosphatase activity is pH-sensitive in vitro and in

cells, and mutation of identified His116 and Glu252 abolishes pH-sensitive function. We also

discovered that Src is an unrecognized pH-dependent kinase and mutation of the identified

ionizable network abolishes pH-sensitive activity. Importantly, we found that Src kinase activity

was pH sensitive even in the presence of EGF and with a phosphomimetic (Src-Y527E) mutant

required for auto-inhibitory SH2 domain binding. Thus, the identified pH-sensitive regulation of

Src kinase activity functions in concert with established mechanisms of Src regulation by

phosphorylation. Constant pH molecular dynamics simulations performed on both SHP2 and Src

support allosteric regulation mediated by pH-dependent binding of inhibitory SH2 domains to

the respective catalytic domains. Finally, we show that evolutionarily conserved putative pH-

sensing networks were identified across SH2 domain-containing signaling proteins. Taken

together, our computational, biophysical, and cellular analyses reveal a role for pHi dynamics in

allosterically regulating activity of modular SH2 signaling proteins to control biology.

Introduction

Transient intracellular pH (pHi) dynamics[1] regulate mammalian proliferation[2, 3], migration[4], and differentiation[5]. However, for many pH-dependent cell processes, the molecular mediators are unknown[6]. All proteins have ionizable residues that can bind or release protons, thereby changing their charged state. For an ionizable residue to have pH-dependent biological function, the H^+ binding affinity (pK_a) of one or more residues must be in the physiological pH range (6.8-8.0). It is not surprising that most cytoplasmic pH-sensitive proteins (pH sensors) with characterized molecular mechanisms function through titratable histidine residues (solution pK_a of 6.5). However, the pK_as of ionizable residues are sensitive to electrostatic microenvironment[7]. Thus, local protein microenvironment can up- or down-shift pK_as of glutamates, aspartates, and lysines into the physiological pH range[8–12]. Further complicating this pH sensing landscape, ionizable residues can cooperatively regulate pH-dependent membrane proteins[13, 14] and can be sequestered within cytoplasmic protein cores or buried at the interface of protein-protein complexes[15]. However, complex networks of ionizable residues are difficult to identify *a priori* based on structure-gazing, and thus many cytoplasmic proteins known to have pH-sensitive function have unknown or incompletely characterized molecular mechanisms.

Results

Pipeline to identify putative pH-sensitive networks

To more quickly identify pH-sensitive proteins and characterize unknown pH sensing mechanisms, we developed an in silico prediction pipeline to identify putative pH sensing nodes based on 3D protein structure (**Fig. 1A**, see methods for details).

Figure 1. New pipeline to identify pH-sensitive networks predicts SHP2 His116 and Glu252
have physiological pK_as. (A) Schematic for in silico pK_a prediction method for proteins with
solved structures. Briefly, all available structures in the protein database are curated, electrostatic
properties are calculated using PROPKA, results are filtered for ionizable residues with
physiologically relevant predicted pK_a values, and data are visualized in a 3D structure or a 2D

residue interaction network. (B) Crystal structure of SHP2 shown in cartoon and surface format
(PDB ID:2SHP). Protein tyrosine phosphatase (PTP) domain colored in grey, SH2 domains
colored in yellow. (C) Structure of SHP2 (PDB ID:2SHP) with protein tyrosine phosphatase
(PTP) domain in grey and SH2 domains in yellow. Residues identified through in silico ionizable
network prediction pipeline shown in spheres. Residues with predicted pK_a shifts (cyan) cluster
with ionizable interactors (magenta) across the phosphatase-SH2 domain interaction interface of
SHP2. (D) Table of predicted pK_as for cyan residues identified using *in silico* ionizable network
prediction pipeline on 47 SHP2 structures (mean ± SD). (E) Residue interaction network of
residues with predicted pK_a shifts (cyan) and their ionizable interactors (magenta). Length of
edges reflect the strength of the coulombic interaction, with stronger coulombic interactions
having shorter edge lengths (F) Zoom of SHP2 structure at the PTP-SH2 interaction interface.
Networked residues from C and E are shown in stick. Residues with predicted pK_a shifts in cyan
and ionizable interactors in magenta.
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Briefly, we use PROPKA(*16*) to predict the pK_as of ionizable groups based on available

structure(s) of a protein of interest. Next, we filter these results for buried ionizable residues with

physiological pK_as and generate 2D and 3D maps showing the identified residue networks and

other ionizable coulombic interactors. We can perform this pipeline on multiple full-length

structures of the protein of interest, increasing the likelihood of identifying functional networks.

Through the generation of interaction network maps and structural maps, our pipeline provides

meaningful perspectives on the functional roles of pH-sensing residues based on their location

and clustering within the protein.

Our pipeline leverages structural flexibility through the analysis of multiple solved

protein structures and integrates PROPKA3 for efficient pKa estimation. Previous studies

collected experimental pK_a values from a diverse set 34 proteins with 290 experimentally

determined pK_as for Asp, Glu, His, Tyr and Lys residues (*17*). Using our pipeline, we calculated

the pK_as for these previously determined ionizable residues and found that our pipeline achieves

high accuracy, with a correlation coefficient of 0.954 and a root-mean-square deviation (RMSD)

of 0.888 (**Fig. S1A, B**). The majority of proteins in this dataset had pK_a shifts of less than 1.5 pH

units, with just a few residues exhibiting shifts of up to 3.5 pH units (*17*). The Garcia-Moreno lab

previously used NMR to measure pK_as of buried ionizable residues in Staphylococcal nuclease

(SNase) mutants, and found large shifts in pKas (up to 5 pH units) from their solution pK_a values

(*18–20*). To determine whether our pipeline can accurately predict large pK_a shifts, we compared

the delta pK_as of the SNase NMR dataset against our predictive pipeline and found that our

pipeline generally had strong correlation values with an overall RMSD of 1.6 pH units (**Fig.**

S1C, D). Furthermore, we found that the pipeline accurately identified whether the residue was

far upshifted or far downshifted. Importantly, there was no bias in pKa calculation errors using

our pipeline for histidines, aspartates, and glutamates compared to experimental pKas in the

SNase dataset. Our pipeline consistently under-predicted lysine pKa shifts compared to

experimental pKas determined for the SNase dataset (**Fig. S1C**), though no such bias was found

for lysine residues in the more diverse protein dataset (**Fig. S2A**).

The performance of our pipeline compares favorably to prior work developing a

computationally complex pKa prediction programs (Rosetta pH, RMSD 0.85) (*17*). While multi-

conformation continuum electrostatic (MCCE) calculations have been frequently used to analyze

pKa shifts based on protein structures (*21*, *22*), MCCE is computationally expensive and does

not achieve improved RMSDs compared to our computationally inexpensive approach. RMSDs

from "quick calculation" MCCE are generally >1.3 pH units, and calculations including rotamers

and side chain optimization are required to achieve RMSDs <1.0 pH unit by MCCE (*21*). Similar

computationally efficient approaches have been developed to predict protein pKas such as

pHinder (*13*) and BRIDGE (*23*), both arising from work on membrane proteins. Unlike these

approaches, our approach is agnostic to protein localization and does not require a path for

structural waters from bulk solvent to the identified buried ionizable networks(*13*, *24*).

Thus, our computational pipeline offers a comprehensive and efficient approach to

identify residues with predicted physiological pKas that may function as pH-sensitive residues in

proteins. Through the generation of interaction network maps and structural maps (**Fig. 1A**), our

pipeline provides meaningful information to identify putative pH-sensing residues and link them

to protein function based on their location and clustering within the protein. We next applied our

pipeline to predict pH-sensing mechanisms and identify novel pH sensitive proteins.

Analysis pipeline applied to SHP2 identifies His116 and Glu252 with predicted upshifted

pK$_a$s

We first applied our analysis pipeline to the SH2 domain-containing signaling protein SHP2.

SHP2 is a regulator of multiple pH-sensitive processes including cell proliferation, migration,

differentiation, growth, and survival(*25–27*). SHP2 has also been shown to have pH-dependent

phosphatase activity in vitro, with optimal activity at pH 7.0 and decreasing activity both below

and above 7.0(*28*), suggestive of multi-group titration. While SHP2 activity is pH sensitive in

vitro, the pH-dependent molecular mechanism has not been identified. Furthermore, prior work

showed that SHP2 activity positively regulates endothelial cell migration and angiogenesis and

vascular smooth muscle cell function(*26*), but the role for pH-sensitive SHP2 function in cells is

less clear.

SHP2 consists of three globular domains: a protein tyrosine phosphatase (PTP) domain

responsible for catalyzing the dephosphorylation of tyrosine-phosphorylated proteins, and two

Src Homology 2 (SH2) domains that serve as phosphotyrosine (pTyr)-recognition domains(*29*)

(**Fig. 1B**). In the absence of a tyrosine-phosphorylated binding partner, the N-terminal SH2

domain binds directly to the phosphatase domain, blocking the active site(*30*). Upon ligand-

induced receptor activation or signaling events, the SH2-PTP interaction is disrupted when the

SH2 domains are displaced by a tyrosine phosphorylated binding partner(*30*). Thus, the SH2

domains control SHP2 activity by allosterically inhibiting the PTP domain in the bound state and

influencing SHP2 localization via direct interactions with phosphorylated binding partners when

signaling active(*30*).

Because SHP2 has no known molecular mechanism of pH-sensing, our goal was to identify

the putative pH sensing nodes driving SHP2 pH-dependent phosphatase activity. We processed

47 structures of SHP2 available in the PDB through the computational pipeline. Importantly, we

did not filter the structural input data: SHP2 structures included active conformations, inhibited

conformations, and SHP2 proteins with gain- or loss-of-function mutations. Our analysis

revealed a conserved network of ionizable residues clustering at the interface between the SH2

and PTP domains of SHP2 (**Fig. 1C**). This residue network contained two residues with

predicted physiological pK_as: His116 and Glu252, with predicted pK_as of 6.8±0.3 and 7.4±0.3,

respectively (**Fig. 1D**). His116 is in the C-SH2 domain and directly interacts with a cluster of

glutamate residues (E121, E139, E232, and E249). Similar glutamate "cages" have been

identified in other wild-type pH sensors including talin(*31*) and RasGRP1(*32*). Glu252 is in the

phosphatase domain at the interaction interface with the N-SH2 domain and interacts with R4,

E249, E258, R498, and E508 (**Fig. 1E, F**). We next determined the structural conservation of the

identified residues using Consurf(*33*). Analyses of structural conservation can frequently reveal

functionally important regions, such as catalytic and ligand-binding sites(*33*). We found that the

C-SH2 and N-SH2 are both highly conserved at the interaction interface with the PTP domain

(**Fig. S2A**). We also determined that His116 and Glu252 are sequence-conserved across SHP2

from lower-order organisms (**Fig. S2A-C**). Taken together, these data suggest that the SH2

domain binding interface in SHP2 has an evolutionarily conserved network of ionizable residues

with predicted physiological pK_as.

SHP2 pH sensitive function requires both His116 and Glu252

We hypothesized that the previously uncharacterized pH-dependent molecular

mechanism of SHP2 requires the ionizable network identified using our computational pipeline.

We first assessed the in vitro phosphatase activity of wild-type SHP2 under different buffer pH

(pH 6.1-8.0) using a generic para-nitrophenyl phosphate (PNPP) substrate. We found that wild-

type SHP2 phosphatase activity is pH dependent, with maximal activity at pH 6.7 and reduced

activity both above and below this value (**Fig. 2A, C, S3A**). We found that k_{cat} increased from

pH 6.1 through 6.7 and decreased from 7.0 through 8.0 forming a biphasic activity curve **(Fig.**

2C), while K_m for the PNPP was pH-insensitive (**Fig. S3A**). This result confirmed previous in

vitro characterization of SHP2 activity(*28*), showing similar apparent pK_as of ~6.7 and ~7.1 in

both the k_{cat} (**Fig. 2A, C, S3B**) and catalytic efficiency (k_{cat}/K_m) pH profiles (**Fig. S3C**).

Reactions with bovine serum albumin (BSA) addition showed no pH-dependence, confirming

that buffer pH is not independently affecting non-enzymatic PNPP hydrolysis in these assays

(**Fig. S3D**). To test whether the identified network is responsible for SHP2 pH-dependent

activity, we generated a SHP2 double mutant where both H116 and E252 were mutated to non-

titratable alanine residues. We repeated the phosphatase assay and found that the activity of

SHP2-H116A/E252A was pH-independent (**Fig. 2B**). While k_{cat} of SHP2-H116A/E252A was

reduced compared to WT SHP2, there was no pH-dependence of k_{cat}, $K_m,$ or catalytic efficiency

(**Fig. 2B, C, S3A, S3C**). This demonstrates that H116 and E252 are required for pH-dependent

activity of SHP2.

Figure 2. Molecular mechanism of SHP2 pH sensing requires both His116 and Glu252. (A)
Wild-type (WT) SHP2 in vitro phosphatase activity curves with increasing concentrations of
generic substrate p-Nitrophenyl Phosphate (PNPP) at buffer pH ranging from 6.1 to 8.0. (mean ±
SEM; N=3 from ≥2 different protein preparations) (B) Double mutant (H116A E252A SHP2) in
vitro phosphatase activity, assays performed as in A. (mean ± SEM; N=3 from ≥2 different
protein preparations) (C) Plot of k_{cat} vs. pH for WT and double mutant (H116A E252A SHP2).
Calculated from activity curves in A and B. (mean ± SEM) (D-E) Single-mutant in vitro
phosphatase activity for (D) H116A-SHP2 and (E) E252A-SHP2. Assays performed as in A.
(mean ± SEM; N=3 from ≥2 different protein preparations) (F) Plot of K_{cat} vs. pH for WT and

single mutant H116A SHP2 and E252A SHP2. Calculated from activity curves in A, D and E.
(mean ± SEM) (G) CpHMD was performed on WT SHP2 at pH values from 4.0-10.0. Shown are
overlapping views of WT SHP2 structures at the start of CpHMD simulation (t = 0 ns) and end
of simulation (t = 8 ns) for pH values 5.0 (grey), 5.5 (cyan), 6.5 (magenta) and 8.5 (yellow). (H)
Average Interdomain center of mass distances for WT and H116A E252A SHP2 for the last 3 ns
of the simulation (I) CpHMD was performed on H116A E252A SHP2 at pH values from 4.0-
10.0. Shown are overlapping views of H116A E252A SHP2 structures at the start of CpHMD
simulation (t = 0 ns) and end of simulation (t = 8 ns) for pH values 5.0 (grey), 5.5 (cyan), 6.5
(magenta) and 8.5 (yellow).

Our in silico pK_a prediction analysis suggests that H116 and E252 function within

networks of conserved ionizable residues. To probe this interaction network in more detail, we

next generated the single point mutants (SHP2-H116A and SHP2-E252A) and found that both

mutants retained pH-dependent phosphatase activity, but each with a single apparent pK_a (**Fig.**

2D-F). For both mutants, k*cat* was maximal at low buffer pH and reduced with increasing pH

(**Fig. 2F, S3A, S3C**). We predicted that the pH-dependent activity observed in the single point

mutants reflects the pK_a of the remaining titratable residue. We compared apparent pK_as of the

mutants and found that SHP2-H116A mutant had an apparent pK_a of 7.5 (**Fig. 2F, S3A, S3E**),

which correlates with the higher apparent (pK_{a2}) of wild-type SHP2 (~7.1) and the in silico

predicted pK_a of E252 (~7.4) (**Fig. 1D**). The E252A mutant has a lower apparent pK_a of 6.8 (**Fig.**

2F, S3A, S3E), which matches the lower apparent (pK_{a1}) of the wild-type SHP2 (~6.7), and the

in silico predicted pK_a of His116 (6.8) (**Fig. 1D).** This suggests that in the H116A point mutant,

E252 drives the observed pH-dependent activity while in the E252A point mutant, H116 drives

the observed pH-dependent activity. Compared to the wild-type SHP2 activity profiles, this

suggests that H116 titration regulates activity between pH 6.1 to 7.0 while E252 titration

regulates activity between pH 7.0 to 8.0. Thus, Glu252 and His116 function cooperatively to

confer wild-type SHP2 pH-dependent activity.

Because E249 interacts with both Glu252 and His116, we next explored the role this

bridging glutamate plays in the pH sensing mechanism of SHP2. Interestingly, we observed

similar pH-dependent activity profiles of SHP2-E249A compared to WT (**Fig. S2A, F**). The

E249A mutant was still pH sensitive with biphasic k_{cat} and catalytic efficiency pH profiles (**Fig.**

S3C, S3G). However, the apparent pK_{a1} and pK_{a2} of the E249A mutant were both shifted higher

(6.8 and 7.7) when compared to wild-type SHP2 (6.7 and 7.1) (**Fig. S3A, S3C**). This suggests

that E249 is not acting as a direct proton conduit or relay between the identified pH sensing

residues (H116 and E252) but instead the presence of E249 tunes the pK_a values of these residues

through the interaction network.

CpHMD reveals pH-dependent residue conformations and SH2 domain release in SHP2

Due to the clustering of pH-sensitive residues at the SH2 and PTP domain interface, we

hypothesized that pH-dependent binding of the inhibitory SH2 domains drives pH-dependent

SHP2 activity. We used continuous constant pH molecular dynamics (CpHMD) to probe pH-

dependent structural conformations of wild-type SHP2. In classical molecular dynamics (MD)

simulations, solvent pH is considered implicitly by fixing protonation states based on empirical

or predicted residue pK_a values. However, protein conformational dynamics may depend

explicitly on residue protonation states, so conventional MD methods cannot capture how

dynamic changes in residue protonation affect structural dynamics. CpHMD addresses this gap

by sampling protonation and conformation states simultaneously(*34*) and lends insight into

proton-coupled mechanisms that are not captured in conventional MD methods.

We performed CpHMD simulations of SHP2 using the GBNeck2 implicit solvent model

for pH values ranging from 4.0 to 10 (in increments of 0.5) (based on(*34*), see methods;

trajectories in **Movies 1-13**). Each simulation was run for 8 nanoseconds, allowing for

convergence of backbone RMSD and protonation states, for an aggregate 104 nanoseconds of

total simulation time. In agreement with the in vitro results, the pK_a values calculated from SHP2

CpHMD showed that H116 had a lower pK_a (6.0) compared to E252 (8.4) (**Fig. S4A, S4B**). In

addition, we observed and quantified coordinated pH-dependent changes in the side chain

conformations of H116 and E252. (**Fig. S4C-D**). At low (4.5) and high (8.5) pH, H116 and E252

are pointed toward each other, but at optimal pH for activity (6.5), E252 flips out and H116

swings in, disrupting its local helix (**Fig. S4C-D**). From the CpHMD trajectories, we noted that

the SH2 domain remains rigid and tightly bound to the PTP domain at pH values less than 5.5

and higher than 8.0 (**Fig. 2G-H**, **Movie4 (2SHP_pH5.5) and Movie9 (2SHP_pH8.0)**).

However, at optimal activity pH (6.5) the SH2 domain is more dynamic and loosely bound to the

PTP domain (**Fig. 2G-H, Movie6 (2SHP_pH6.5)**). To assess interdomain conformations, we

quantified the center of mass distances between the N-SH2 or C-SH2 domain and the PTP

domain during the final 3 nanoseconds of the trajectories. We found distinct pH-dependent

dynamics between the N-SH2 and PTP domain, with maximal interdomain distances (65Å) at pH

6.5 and minimal distances (30Å and 35Å) at pH 4.5 and 8.5 respectively (**Fig. 2H, S4E**). We

observed that dynamics between the C-SH2 and PTP domain followed the same pH-dependent

trend, with maximal distances (54Å) achieved at pH 6.5 (**Fig. 2H, S4F**). While interdomain

orientations were not included in this analysis, the interdomain distance trends alone suggest pH-

dependent SH2 domain release and are in striking agreement with pH-dependent in vitro WT

SHP2 activity experiments.

We also performed CpHMD simulations for the H116A E252A SHP2 mutant using the

same protocol as for WT to determine if these mutations also abrogate the pH dependent

interdomain dynamics in silico. Encouragingly, we observed that double mutant exhibited a more

closed domain conformation when compared to WT across the pH range 6.0-8.0 (**Fig. 2 H-I,**

S5A-C). Importantly, the double mutant did not exhibit the strong pH-dependent inter-domain

dynamics that we observed with WT SHP2 (**Fig. 2H-I**). Our CpHMD results indicate a loss of

pH-dependent interdomain dynamics in the mutant protein, which is in agreement with the in

vitro activity results. Taken together, our CpHMD data support a molecular mechanism by which

WT SHP2 has pH-dependent SH2 domain binding, with His116 and E252 being required for pH-

dependent SH2 domain conformational dynamics.

Intracellular pH regulates SHP2 activity and downstream signaling in MCF10A cells

We next determined whether SHP2 activity is regulated by physiological pH changes in

cells. We first experimentally manipulated intracellular pH (pHi) in normal breast epithelial cells

(MCF10A), using inhibitors of the sodium proton exchanger (EIPA) and sodium bicarbonate

transporter (S0859) to lower pHi from 7.45±0.12 to 7.10±0.01 and 30 mM ammonium chloride

to raise pHi to 8.00±0.27 (**Fig. 3A**). After one hour of pHi manipulation, we assayed for

endogenous SHP2 basal activity by immunoblotting for phosphorylation of SHP2 at tyrosine 542

(Y542), which is required for activity(*35*). We found that endogenous SHP2 activity is pH

sensitive, with increased pY542 levels at low pHi and decreased activity at high pHi compared to

control (**Fig. 3B, C**). To investigate downstream signal transduction, we measured SHP2 binding

to its signaling-active binding partner, Gab1(*36*) using a co-immunoprecipitation assay. SHP2

immune complexes contained significantly more Gab1 when pHi was low compared to control

and high pHi (**Fig. 3B, D**). This demonstrates that endogenous SHP2 has pH-dependent activity

in MCF10A cells, with higher activity and binding to the Gab1 signaling partner at low pHi

compared to control and high pHi.

Figure 3. Intracellular pH regulates SHP2 activity and downstream signaling in MCF10A cells (A) pHi measurements of MCF10A cells. Cells were treated with 25 μM EIPA + 30 μM S0858 for 1 hour to lower pH to 7.10. To raise pHi, cells were treated with 30 mM ammonium chloride for 1 hour to raise pH to 8.00. Untreated cells had a pHi of 7.45. Scatter plot shows (median ± interquartile range, N =10) (B) Representative immunoblots of SHP2, Gab1, and phospho-SHP2 (pY542) from SHP2 immune complexes (SHP2 IP) or whole cell lysates (Cell Lysate) isolated from MCF10A cells prepared as in A. (C-D) Quantification of phospho-SHP2 (C) and Gab1 Co-IP (D) for replicate data collected as in B. Data was normalized to control in each biological replicate. Scatter plot shows (mean ± SEM, N=4) in C and (median ± IQR, N=7) in D. (E) Representative images of MCF10A cells expressing the SHP2 activity reporter (Grb2 TagBFP) pseudocolored on an intensiometric scale. Images show cells prior to manipulating pHi with nigericin buffer (Pre-Nigericin) (see methods for details), 50s after manipulating pHi, and 900s after manipulating pHi. Scale bars: 25μm (F) Quantification of images collected as in E. Membrane intensity of SHP2 activity reporter over time was photobleach-corrected and then normalized to initial intensity. Line trace shows (mean ± SEM) from single-cell data (6.7 pH, n=30, 7.4 pH, n=30, 7.8 pH, n=25, control, n=28) collected across N=3 biological replicates. (G) Quantification of endpoint membrane intensities of single cells collected as described in F. Scatter plot shows (median ± interquartile range, N = 5) (H) Representative immunoblot of lysates prepared from MCF10A cells expressing either WT SHP2 or H116A E252A SHP2. Immunoblots show total and pY542-SHP2 under low, control, and high pHi conditions. (I) Quantification of replicate data collected as in H. Scatter plots show (mean ± SEM, N=3). Intensities were normalized to the corresponding control condition. For A and G significance was determined using the Kruskal-Wallis test. For C and I significance was determined using a ratio paired t-test to compare between treatment conditions and a one-sample t-test to compare to control. For D significance was determined using a Wilcoxon test to compare between treatment conditions and a Wilcoxon sign-ranked test to compare to control. * p<0.05, **p<0.01, ***p<0.001, ****p<0.0001.

We next confirmed the effect of pHi dynamics on basal activity of endogenous SHP2

using a live, single-cell reporter of SHP2 activity (tagBFP-Grb2)(*37*). We validated that the

tagBFP-Grb2 reporter was robustly recruited to the cell membrane upon EGF stimulation (active

SHP2) and that this recruitment was abolished by both a specific SHP2 inhibitor (PHPS)(*38*) and

an upstream EGFR inhibitor (Erlotinib) (**Fig. S6A**). We also validated inhibitor efficacy and

specificity using western blots to assess EGFR and SHP2 phosphorylation (**Fig. S6B**). Erlotinib

treatment reduced EGF-induced pEGFR (pY1068; Grb2 phosphosite) and pSHP2 (pY542),

whereas PHPS reduced pSHP2 while leaving pEGFR levels unaffected (**Fig. S6B**). These data

show that membrane recruitment of the biosensor is dependent on SHP2 activity.

After validating tagBFP-GRB2 as a specific SHP2 activity biosensor, we next measured

biosensor recruitment to the MCF10A cell membrane under basal (unstimulated) conditions with

and without pHi manipulation using the protonophore nigericin (see methods for details). When

the pHi of the MCF10A cells was pinned to 6.7, we observed increased biosensor recruitment to

the cell membrane, indicating increased SHP2 activity (**Fig. 3E-G).** Conversely, we observed no

change in biosensor recruitment when MCF10A cell pH was pinned to basal pHi conditions (7.4)

and reduced biosensor recruitment when the pHi of MCF10A cells was pinned at 7.8 (**Fig. 3F-**

G). Importantly, initial biosensor intensity at the membrane was not different prior to nigericin-

based pHi manipulation (**Fig. S6C**) and increased biosensor recruitment at low pHi was

abolished with the addition of PHPS (**Fig. S6D**). This shows that endogenous SHP2 basal

activity is sensitive to pHi dynamics in single living cells.

To confirm that the pH sensing network of H116 and E252 mediates pH-dependent SHP2

activity in cells, we overexpressed HA-tagged WT SHP2 and SHP2-H116A/E252A in MCF10A

cells and quantified SHP2-pY542 levels with and without pHi manipulation. We found that

overexpressed WT SHP2 recapitulated the endogenous SHP2 results, with increased activity

(SHP2-pY542) at low pHi and decreased activity at high pHi compared to control MCF10A

(**Fig. 3H, I**). As expected, the double mutant SHP2-H116A/E252A had pH-independent activity

(SHP2-pY524) in MCF10A (**Fig. 3H, I**), confirming that His116 and E252 are required

mediators of pH-sensitive SHP2 activity. Through our cell-based analyses, we show that SHP2

activity is sensitive to physiological changes in pHi, with increased basal activity at low pHi, and

that H116 and E252 mediate pH-dependent activity of SHP2.

pH sensing nodes cluster at SH2 interface in other SH2 signaling proteins

SH2 domains are modular signaling domains that bind to phosphotyrosine residues,

which have experimentally determined pK_as that are close to physiological (5.7-6.1)(*39, 40*) and

are highly structurally and sequence-conserved across signaling proteins(*29*). We hypothesized

that networks of residues with physiological pK_as serve a functional role in regulating pH-

dependent SH2 binding to phosphotyrosine residues across SH2 domain-containing proteins. To

explore this, we applied our in silico computational pipeline to a collection of SH2 domain-

containing proteins with multiple solved structures. We found that 90% of SH2 domain-

containing proteins tested had ionizable residue networks with pK_as predicted to be shifted into

the physiological pH range (**Fig. S7**). As we observed with SHP2, these ionizable residue

networks clustered at the SH2 binding interfaces (**Fig. S7**). Interestingly, we observed this

pattern of clustering across functional protein classes—finding it in phosphatases (SHP1) (**Fig.**

S7A), kinases (ZAP70, JAK1 JAK2, and ABL1) (**Fig. S7B-D, H**), transcription factors (STAT6,

STAT5A) (**Fig. S7E-F**), and GTPase activating proteins (CHIO) (**Fig. S7G**).

As a control, we also analyzed a collection of SH3 domain-containing signaling proteins.

SH3 domains are modular signaling domains that are similarly highly evolutionarily and

structurally conserved(*41*), but bind proline-kink regions(*42*) where electrostatics should not

drive function. While we identified ionizable networks with physiological pK_as in some SH3

domain-containing proteins, the shifted residues did not cluster at the binding interfaces of SH3

domains (**Fig. S7H, S7I-K**). This analysis suggests that ionizable networks with upshifted pK_as

are not a general feature of all signaling domain interaction interfaces but instead are enriched at

functional SH2 domain interfaces.

Analysis pipeline applied to Src identifies four networked ionizable residues with predicted

physiological pK$_a$s

We next selected one of the hits from the screen of SH2 domain-containing signaling

proteins (Src) to further validate the role of pH in the allosteric regulation of SH2 domain-

containing signaling proteins. The signaling kinase Src has three globular domains: a kinase

domain (SH1), an inhibitory SH2 domain that binds phosphotyrosines, and an inhibitory SH3

domain that binds proline-rich regions (**Fig. 4A**). The SH2 domain inhibits kinase activity when

bound intramolecularly to the C-terminal phosphotyrosine (pY527)(*42*). However, when the SH2

and SH3 domains are released, pY527 is dephosphorylated, the activation loop unfurls, and the

SH1(kinase) domain autophosphorylates a conserved tyrosine (Y416) in the activation loop (A-

loop). Activation loop unfolding and phosphorylation are required for full activation and

facilitate Src binding to downstream targets(*42*).

We processed seven structures of Src available in the PDB through the computational

pipeline. Our analysis identified 5 residues predicted to have physiological pK$_a$s: C185 (pK$_a$ of

7.7 ± 0.0), H201 (pK$_a$ of 7.8 ± 0.1), E454 (pK$_a$ of 6.9 ± 0.4), H492 (pK$_a$ of 7.0 ± 0.5), and E524

(pK$_a$ of 7.3 ± 0.4) (**Fig. 4B, C**). Four residues (C185, H201, E524, and H492) are networked in a

cluster at the interface between the SH2 domain and the kinase domain (**Fig. 4B, C**). E524 is in

the C-terminal tail of Src and electrostatically interacts with H201 and C185 in the SH2 domain

through bridging glutamate residues (E159, E178) and interacts with H492 in the kinase domain

through a bridging aspartate residue (D493) (**Fig. 4B, C**). While E454 has a predicted

physiological pK$_a$, it is in the kinase catalytic site and distant from the SH2 regulatory domain

interface (**Fig. 4B**). This analysis of Src again demonstrates that ionizable residue networks with

predicted physiological pK$_a$s cluster at SH2 but not SH3 domain interfaces.

A

C

Cyan- pKa-Shifted Residues   Yellow- SH2 Domain
Magenta- Ionizing Interactors   Green- SH3 Domain

B

Residue	Solution pKₐ	Predicted pKₐ	Domain
Cys185	9	7.7 ± 0.0	SH2
His201	4.5	7.8 ± 0.1	SH2
Glu454	4.5	6.9 ± 0.4	Kinase
His492	6.5	7.0 ± 0.5	Kinase
Glu524	4.5	7.3 ± 0.4	Kinase

Cyan- pKa-Shifted Residues
Magenta- Ionizable Interactors
— Coulombic Interaction

D

Figure 4: *Residues with predicted physiological pK$_a$ shifts cluster at the binding interface of the SH2 and kinase domains in Src* (A) Crystal structure of pilot protein Src shown in cartoon and surface format (PDB ID:2SRC). Kinase domain colored in grey, SH2 domain colored in yellow, and SH3 colored in green (B) Table of predicted pK$_a$s for shifted residues (mean ± SD). Residue interaction network of residues with predicted pK$_a$ shifts (cyan) and their coulombic ionizable interactors (magenta). Edge length reflects the strength of the interaction, with stronger coulombic interactions having shorter edge lengths. (C) Structure of Src (PDB ID:2SRC) showing the kinase domain in grey, SH2 domain in yellow, and SH3 domain in green. Residues identified through in silico ionizable network prediction pipeline shown in spheres. Residues with predicted pK$_a$ shifts (cyan) cluster with ionizable interactors (magenta) across the kinase-SH2 domain interaction interface of Src. Zoom in shows Src structure at the kinase-SH2 domain interaction interface. Networked residues from B and C are shown in stick: residues with predicted pK$_a$ shifts in cyan, interactors in magenta. (D) CpHMD (see methods for details) was performed on Src at pH values from 4.0-10.0. Shown are overlapping views of Src structures at the start of CpHMD simulation (t = 0 ns) and end of simulation (t = 8 ns) for pH values 6.0 (grey), 7.0 (cyan), 7.5 (magenta) and 8.5 (yellow).

We determined the structural conservation of the identified residues in Src and found very high structural conservation of the ionizable network region and individual residues (**Fig. S8A-C**). The COSMIC database(*43*) also showed recurrent somatic mutations at each of these sites: C185, H201, H492, and E524 (**Fig. S8D**). Recurrent charge-changing somatic mutations were found in H201, H492, and E524 (Fig S8D, E), suggesting functional importance of the identified network and potential for pH-sensitive network disruption in cancer.

CpHMD reveals pH-dependent residue conformations and SH2 domain release in Src

We next assessed pH-dependent structural dynamics in Src using CpHMD (see methods; trajectories in **Movies 14-26**). While we were not able to generate a pK$_a$ for C185 using the CpHMD trajectories (**Fig. S9A**), all other identified residues had upshifted and near-physiological pK$_a$s calculated from the CpHMD trajectories: (H201, pK$_a$ of 7.3; E454 pK$_a$ of 8.2; H492 pK$_a$ of 7.0; E524 pK$_a$ of 6.8) (**Fig. S9B-E**). Local side chain movement showed pH-dependent changes in the identified residue network, suggesting pH-dependent interaction pairs

(**Fig S9F, G**). Dihedral angles change with pH for all identified residues, with coupled dynamics

observed for connected residues (H201, C185, and H492) between pH 6.5 and 7.5 while E524

dihedral angles change at pH values above 7.0 (**Fig S9F**). The CpHMD trajectories also show

pH-dependent changes in interdomain interactions between the Src kinase domain and the

inhibitory SH2 and SH3 domains (**Fig. 4D**). In agreement with the SHP2 dynamics, the SH2

domain of Src was bound more tightly to the kinase domain at high pH (8.5) compared to low

pH (6.0), where both the SH3 and SH2 domain were unbound (**Fig. 4D, Movie18**

(2SRC_pH6.0), Movie23 (2SRC_pH8.5))). We also observed intermediate domain

conformations in the pH 7.0 and pH 7.5 trajectories, with Src adopting a conformation where the

SH3 domain binds tightly while the SH2 domain is more dynamic (**Fig 4D, Movie20**

(2SRC_pH7.0), Movie21 (2SRC_pH7.5))). To assess interdomain conformations, we quantified

interdomain distances between either the SH2 or SH3 domain and the central kinase domain of

Src during the final 3ns of the trajectories. We found pH-dependent SH2-kinase interdomain

distances with a maximum (least binding) at pH 6.0 and minimums (tight binding) at high (8.5)

and low (4.5) pH (**Fig. S9H**). We observed similar pH-dependent trends in pH-dependent SH3-

kinase interdomain distances, with a maximum (least binding) distance at pH 5.5 and minimums

at high (8.5) and low (5.0) pH (**Fig. S9I**). To rule out general pH-dependent structural

compaction in these CpHMD trajectories, we also assessed SH3-SH2 domain distances and

found no pH dependence (**Fig. S9J**). While these short trajectories are less likely to capture large

protein domain movements, the trends across the SHP2 and Src CpHMD analyses are strikingly

consistent: low physiological pH (6.0-7.0) leads to SH2 release from the catalytic domain

compared to high physiological pH (7.0-8.0) where SH2-catalytic interdomain interactions are

increased.

Intracellular pH regulates Src activity and signaling in MCF10A cells

We next determined whether basal kinase activity of endogenous Src is sensitive to

physiological pH changes in normal epithelial cells. We assessed Src activity by immunoblot

quantification of the levels of pY527, a proxy for inhibited Src, and pY416, a proxy for active

Src (**Fig. 5A**). We found that endogenous Src activity was pH sensitive, with increased activity at

low pHi compared to control and high pHi (**Fig. 5B-D**) with no change to total endogenous Src

levels (**Fig. S10A**). Importantly, the pH-dependent trends in pY527 and pY416 both support the

hypothesis that low pHi leads to SH2 domain release, loss of the inhibited Src phosphosite

(pY527) (**Fig. 5C**), and gain of the active Src phosphorylation site (pY416) (**Fig. 5D**). Next, we

performed immunofluorescence labeling and single-cell analysis of Src activity in MCF10A cells

and found that active Src (pY416) was increased at low pHi and decreased at high pHi compared

to control cells (**Fig. 5E-G, S10B, C**). We stimulated cells with EGF to determine how pHi

regulates Src in the context of growth factor stimulation. We observed significant increases in

Src activation (pY416) in EGF stimulated control cells, demonstrating that growth factor

stimulation can drive increased Src activation (**Fig. 5E-G**). Interestingly, there was no difference

in pY416 levels at low pHi compared to control cells stimulated with EGF, suggesting low pHi

phenocopies Src activation via growth-factor stimulation (**Fig. 5E-G**). However, when high pHi

cells were stimulated with EGF, activation of Src was lower compared to control cells both with

and without EGF stimulation (**Fig. 5E-G, S10B, C**). This indicates that high pH inhibition of Src

is sufficient to attenuate the growth factor receptor activation of endogenous Src.

Figure 5. *Intracellular pH regulates Src activity and localization in MCF10A cells* (A) Cartoon of Src activation (B) Representative immunoblot from MCF10A lysates prepared from cells maintained for 1 hour at low or high pHi or untreated (control). Immunoblots show total Src and indicated Src phosphorylation sites that reflect protein activation pY527 (inactive) and pY416 (active). (C-D) Quantification of pY527 (inactive) (C) and pY416 (active) (D) Src from replicate data collected as in B. Data was normalized to control in each biological replicate. Scatter plots show (mean ± SEM, N=5) (E) Representative confocal images of MCF10A cells fixed and stained for total Src and pY416 (active) Src at given pHi with and without EGF stimulation (10 ng/mL for 5 minutes). Total Src and pY416 are shown in inverse mono intensity display. In the merged overlay, total Src is shown in magenta and pSrc is shown in green, areas of high co-localization show white. Scale bar: 25μm. (F) Quantification of single-cell data collected as in E. Levels of pY416 Src are normalized to total Src in each single cell and to control for each biological replicate. Violin plot shows individual cells as points and (median ± IQR, Low, n=984, Control, n=938, High, n=903, Low + EGF, n=525, Control + EGF, n=595, High + EGF, n=599) collected from 6 biological replicates for - EGF conditions and 3 biological replicates for + EGF conditions. (G). Histogram and zoomed in view of single cell data for data shown in F. Low pHi treatment conditions shown in cyan, control in black, and high pHi treatment shown in magenta. For C and D, significance was determined using a ratio paired t-test to compare between treatment conditions and a one-sample t-test to compare to control. For F, significance was determined using the Kruskal-Wallis test. * $p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$.

It was at first surprising that growth factor stimulation at low and high pHi did not further increase Src activation (pY416) compared to unstimulated cells with matched pHi (**Fig. 5F**). However, when comparing pY416 Src distributions, we did observe statistically significant differences between EGF stimulated and unstimulated cells across all pHi conditions (**Fig. S10B, C**). Our data suggest that pHi manipulation can modulate Src activity in the context of growth factor signaling as well as in basal state.

To determine cellular outcomes of pHi-dependent Src activation, we next assessed downstream signal transduction by monitoring downstream activation of ERK (pT202/ pY204) and E-cadherin (pY685). In both cases, pathway activation downstream of Src recapitulated the pH-dependent activity trends, with increased activation at low pHi and decreased activation at high pHi compared to control cells (**Fig. S10D-G**). In control cells, EGF stimulation produced statistically significant increases in downstream activation of ERK (pT202/ pY204) and E-

cadherin (pY685) (Fig S10D-G). With EGF stimulation, there was no difference in downstream

pathway activation at low pHi compared to control, again suggesting maximal activity is

achieved (**Fig. S10D-G**). Finally, high pHi produced lower downstream activation both with and

without EGF stimulation compared to matched control conditions (**Fig. S10D-G**). This indicates

that low pHi phenocopies EGF stimulation of control cells while high pHi inhibition of Src can

attenuate pathway activation even in the presence of extracellular growth factor.

537   To determine whether the identified residue network in Src mediates pH-dependent

activity, we overexpressed either FLAG-tagged WT-Src or the quadruple mutant Src-

C185A/E454A/H492A/E524A in MCF10A cells. We then quantified pY527 and pY416 levels

with and without pHi manipulation by immunoblot. We found that overexpressing WT Src

recapitulated the pH-dependent endogenous Src activity results, with decreased phosphorylation

of the inhibitory phosphosite (pY527) at low pHi and increased pY527 at high pHi compared to

control MCF10A (**Fig. 6A, B**). As with endogenous Src, we also observed pHi-dependent

phosphorylation of pY416, with increased active Src (pY416) at low pHi compared to control

and high pHi (**Fig. 6A, C**). Taken together, these data demonstrate that pHi allosterically

regulates Src inside cells, with low pHi promoting the active state (pY416, Y527) while high pHi

promotes a more inhibited state (Y416, pY527). As expected, the quadruple Src mutant had pH-

independent phosphorylation of both pY416 and pY527 while maintaining measurable catalytic

activity (**Fig. 6A-C**). Our cell-based analyses show that Src activity is sensitive to physiological

pHi changes, with increased activity at low pHi, and that the identified ionizable residue cluster

is required for pH-dependent Src activity.

554
Figure 6. *Src pH-dependent activity requires an intact ionizable residue network (C185 H201*
H492 E524) (A) Representative immunoblot from MCF10A lysates expressing either WT Src or
the Quad Mutant (Src- C185A/H201A/H492A/E524A) and maintained for 1 hour at low or high
pHi or untreated (control). Immunoblots show total Src and indicated Src phosphorylation sites
that reflect protein activation pY527 (inhibited) and pY416 (active). (B) Quantification of
pY527 (inactive) from replicate data collected as in g. Data was normalized to control in each
biological replicate. Scatter plots show (mean ± SEM, N=3) (C) Quantification of pY416 (active)
from replicate data collected as in g. Data was normalized to control for each biological
replicate. Scatter plots show (mean ± SEM, N=3) (D) Representative immunoblot from MCF10A
lysates expressing either WT Src, Y527A Src, or Y527E Src and maintained for 1 hour at low or
high pHi or untreated (control). Immunoblots show total Src and indicated active Src
phosphorylation site (pY416). (E) Quantification of pY416 (active) from replicate data collected
as in D. Data was normalized to WT control for each biological replicate. For B and C,
significance was determined using a ratio paired t-test to compare between treatment conditions
and a one-sample t-test to compare to WT control. For E, significance was determined using a
one-way ANOVA and a one-sample t-test to compare to WT control. * p<0.05, **p<0.01,
***p<0.001, ****p<0.0001.
572

To further probe contributions of individual residues in the identified residue network to

pH-sensitive Src activity, we generated single point mutants (Src-C185A, Src-E524A, Src-

H201A, and Src-H496A) and measured their activity in MCF10A cells. First, we found that the

E524A mutant pushed Src into a more active, but still pH-dependent, state: Y527 was

significantly dephosphorylated compared to WT Src and pH-independent while Y416

phosphorylation was still pH-dependent but increased compared to WT (**Fig. S11A-C**). This

suggests E524 is required for the observed pH-dependence of pY527 in wild-type Src: without

E524, affinity for pY527 is reduced and the Src C-terminal tail release from the SH2 domain is

pH-insensitive in the physiological range. We can also conclude from the E524A data that the

remaining residue network (C185, H201, and H495) is sufficient to preserve pH-dependent

phosphorylation of active-loop residue (Y416) (**Fig. S11A-C**).

584   We found that C185A and H496A still exhibited trends of pH-dependent phosphorylation

of both Y527 and Y416 (**Fig. S11A-F**), suggesting C185 and H496 are not essential for either

pH-sensitive phosphorylation event on Src. However, because we cannot easily titrate across

wider pHi ranges in these cells (e.g. 6.1-8.0), we cannot rule out the possibility that C185 and

H496 may be critically important for tuning the pKa of the entire residue network. Finally, the

H201A mutant locked Src into an inhibited and pHi-independent conformation, with

significantly reduced Y416 phosphorylation compared to WT (**Fig. S11D-F**). This suggests

H201 plays a predominant role in regulating the pH-dependent active-loop phosphorylation of

Y416 observed in both WT and Src-E524A.

593   Finally, to determine the specific role pH plays in regulating the well-characterized (*44*,

45)phospho-tyrosine activation of Src, we assessed pH-dependent Src activity with Y527

phosphomimetic mutants. We mutated Y527 to a non-titrating alanine that mimics a

constitutively dephosphorylated Y527 and to a titratable glutamate that mimics a constitutively

phosphorylated Y527. As expected, Src-Y527A was constitutively active (high pY416) and pH-

independent (**Fig. 6D,E**). This data phenocopies Src constitutive activation when Y527 is

mutated or deleted (*44*). Conversely, we found that Src-Y527E activation was still pH dependent,

with higher activity at low pHi and lower activity at high pHi when compared to control (**Fig.**

6D,E). Taken together, these data suggest phosphorylation of Y527 contributes to the

modulation of pH-dependent wild-type Src activation. Thus, our data suggest pHi dynamics

function as a rheostat to modulate WT Src activity in concert with traditional modes of Src

regulation (phosphorylation).

Discussion

Our data show that our in silico analysis pipeline can be used to predict and

mechanistically probe pH-dependent protein function. We applied this analysis to characterize

molecular mechanisms of pH-dependent allostery for the known pH sensor SHP2 (**Fig. 7A**). We

find that physiological changes in pHi (0.1-0.4 pHi units) can produce 2-3 fold changes in basal

SHP2 activity. We also used our computational pipeline to identify novel pH regulation of Src

activity and identify the critical pH sensing residues (**Fig. 7B**). Importantly, we showed that the

pH sensitive regulation of Src functions in concert with the well-characterized mode of

phosphorylation (pY527) regulation. For example, simply lowering pHi can phenocopy Src

activation growth factor stimulation and low pH can activate Src even when a phosphomimetic

auto-inhibitory mutant is used (Src-Y527E). These data suggest that the transient pHi dynamics

previously reported during cell cycle progression (0.1-0.2 pH units) (*2*, *46*), cell migration (~0.3

pH units) (*4*, *47*, *48*) and cell differentiation (~0.4 pH units) (*49*) may be sufficient to regulate

basal cell signaling state of SHP2 and Src.

Figure 7. *Molecular mechanism of pH-dependent allostery of SHP2 and Src* (A) Schematic of
pH-driven activation and inhibition of SHP2. At low pH, the SH2 domain is unbound and SHP2
becomes signaling active with increased phosphorylation of Y542, increased GAB1 binding, and
increased Grb2 recruitment. (B) Schematic of pH-driven activation and inhibition of Src. At low
pH, the SH2 domain is unbound and Src becomes signaling active with increased
phosphorylation of Y416, decreased phosphorylation of Y527, and increased substrate
phosphorylation and downstream activation.

We also demonstrated that ionizable residues with predicted physiological pK$_a$s are

conserved across many SH2 domain-containing signaling proteins including kinases,

phosphatases, transcription factors, and GTPase activating proteins. For multi-functional proteins

that contain both evolutionarily conserved SH2 and SH3 domains, the residue networks with

predicted physiological pKas clustered specifically at the interfaces between SH2 and the

functional domains. This suggests that SH2 domains may be primed for pH sensitive allosteric

regulation of signaling proteins. Our data showing the pH-dependence of Src under growth factor

stimulation in cells and when using phosphomimetic mutants also suggests that pH-dependent

regulation of SH2 signaling proteins may function in concert with traditional growth factor

signaling and phosphorylation-dependent regulation. Future work will expand on this hypothesis

with more mechanistic detail and functional validation.

We show that our prediction pipeline is as accurate as more computationally expensive

prediction methods and does not require crystallographic waters or paths to solvent to identify

residue networks. Our pipeline is also modular, enabling incorporation of improved pK_a

prediction algorithms (e.g. recent machine learning (ML) pipelines with improved accuracy over

PROPKA)(*50*). Most characterized pH-sensitive proteins have simple mechanisms where a

single histidine residue titrates with changes in pH to confer changes in protein structure and

function. We applied our network analysis to accurately identify previously validated pH-sensing

residues based on existing structures, including in mutant p53 (His273)(*51*) and the sodium

proton exchanger (H544)(*52*) (**Fig. S12**). We also showed that our pipeline accurately identified

one of the only validated complex multi-site pH sensing mechanisms in isocitrate dehydrogenase

1 (D273, E304, K217)(*53*) (**Fig. S12**) this network was first reported using the more

computationally expensive pHinder program to predict residues with physiological pKas (*53*).

Interestingly, recent work has suggested that His242 is required for pH-sensitive activity of

phosphofructokinase muscle isoform (PFKM), but mutation of this residue did not completely

abrogate the pH sensitive activity of PFKM (*54*). Our network analysis indicates that PFKM has

two networked residues with physiological pKa (His242 and Asp309) (**Fig. S12**) and suggests

that mutating both residues may fully abrogate pH-dependent PFKM function.

Scientists can apply our in silico approach to improve our mechanistic understanding of

pH-dependent cell behaviors lacking known pH-sensitive molecular drivers, including

differentiation(*49*, *55*), cell cycle progression(*2*, *3*), and epithelial to mesenchymal transition(*56*,

57). In addition to revealing the pH-dependent structural proteome, this approach can be applied

to molecularly characterize how dysregulated pHi drives pathophysiology in cancer (increased

pHi)(*6, 58*) and neurodegeneration (decreased pHi)(*59*).

Materials and Methods

pK$_a$ prediction method

All full-length structures for proteins of interest were first identified based on the gene search

and downloaded from the Protein Database (https://www.rcsb.org/). Next, the electrostatic

properties for each structure were calculated using the APBS (Adaptive Poisson-Boltzmann

Solver) webserver (https://server.poissonboltzmann.org/). The APBS calculation was performed

using the following parameters: The pH for continuum electrostatic calculations was set to 7.4.

The AMBER forcefield was used for the minimization step. We set the parameters in the APBS

webserver to ensure that new atoms were not rebuilt too close to existing atoms and that

hydrogen bonding networks were optimized during the structure repair and refinement step. The

electrostatic data for each individual structure was combined into a single dataset and ionizable

residues were then filtered for physiologically relevant pK$_a$s. Histidine residues with pK$_a$s above

7.0 were considered physiologically relevant while aspartates, glutamates, and lysines were

filtered if pK$_a$s were between 6.8.00. For ionizable residues that were classified using these

criteria as "shifted" in $\geq$ 50% of structures, residue pK$_a$s were averaged across all structures in

the dataset. Next, the strength of coulombic interactions for the shifted residues were averaged

for all structures. Structural visualization was done using Pymol and residue interaction networks

were generated in Python (https://zenodo.org/records/15338058). For residue interaction

networks, the length of the connecting lines indicates the strength of the coulombic interactions,

with stronger coulombic interactions having shorter vectors.

pK$_a$ prediction benchmarking

A diverse set of experimental pK$_a$ values were collected for Asp, Glu, His, Tyr and Lys from

previous studies (*17*). The experimental dataset contained 34 proteins with 290 experimentally

determined pK$_a$s. Using our pipeline, we calculated the pK$_a$s of these previously determined

ionizable residues. We then calculated the weighted correlation coefficient for then predicted

pK$_a$s against the experimental pK$_a$s and the Root Mean Squared Deviation (RMSD) of the

predicted pK$_a$ from the experimental values. The Garcia-Moreno lab have also calculated far-

shifted pK$_a$s for ionizable residues in Staphylococcal nuclease (SNase) (*18–20*). To determine if

our pipeline was able to accurately predict these large pK$_a$ shifts, we also generated a dataset

comparing the delta pK$_a$s of the validated dataset against our predictive set and calculated

correlation coefficients and RMSDs from the experimental values.

Structural conservation

The ConSurf server was used as a bioinformatics tool to estimate evolutionary conservation in

proteins of interest. To determine the evolutionary conservation in our proteins of interest, we

followed the recommended guidelines outlined by Yariv *et al.*, 2023(*33*). Briefly, the SHP2

(PDB: 2SHP) and Src (PDB:2SRC) protein structures were submitted to the ConSurf Web server

(https://consurf.tau.ac.il/). ConSurf server utilizes an empirical Bayesian algorithm for

conservation scores ranging from 1 to 9; where 1 is variable and 9 is conserved.

Purification of SHP2 proteins

Full-length SHP2 variants were cloned into the pGEX-4TI SHP2 WT plasmid(*60*), pGEX-4T1

SHP2 WT was a gift from Ben Neel (Addgene plasmid # 8322 ; http://n2t.net/addgene:8322 ;

RRID:Addgene_8322)) and expressed in *E. Coli* for purification. Transformed BL21(DE3) cells

were grown in Miller's Modified Luria Broth (RPI, L24080-2000) supplemented with 0.1

mg/mL ampicillin at 37°C with shaking (250 rpm). When cells reached an OD600 of 0.6,

proteins were induced with Isopropyl β- d-1-thiogalactopyranoside (IPTG) (Thermo Scientific,

R0392) (0.42 mM) and incubated at 18°C overnight with shaking (250 rpm). The induced

cultures were centrifuged at 10,000 rpm at 4°C for 30 mins and resuspended in lysis buffer (B-

PER™ Bacterial Protein Extraction Reagent (Thermo Scientific, 78243)) supplemented with

EDTA-free Protease Inhibitor Cocktail (Roche, 04693132001)). Cell lysates were placed on a

rocker at 4°C for 10 mins before centrifugating at 40,000 rpm at 4°C for 40 minutes. The

supernatant was separated, and glutathione resin (GenScript, L00206) was added to bind the

GST tagged proteins. The mixture was rocked for an hour at 4°C and then purified in a

CrystalCruz chromatography column (Santa Cruz, sc-205554) at 4°C. Purified proteins were

dialyzed into dialysis buffer (20mM Tris 50mM NaCl 1mM DTT 5% glycerol, pH 7.5) overnight

at 4°C and stored at -20°C.

Phosphatase activity assays

SHP2 variants were quantified by measuring absorbance at 280 nm and comparison with BSA

protein standards. Para-nitrophenyl phosphate (pNPP) (Thermo Scientific, 34045) was used as an

artificial substrate for the protein tyrosine phosphatase (PTPase) activity of each SHP2 variant.

Reactions were performed at 30°C in 100 μl volume of PTPase buffer (25 mM Tris–HCl, 50 mM

NaCl, 2 mM EDTA and 10 mM dithiothreitol). Concentrations of pNPP ranged from 12-400 mM

(12, 15.6, 25, 31.2, 50, 62.5, 100, 125, 250, 300, 400) and assay buffer pH values ranged from

6.1 to 8.0. All assay conditions were performed in technical duplicates in 96-well plates.

Reactions were initiated by the addition of 5μg of WT or mutant SHP2 to the reaction mixtures.

Kinetic absorbance readings were collected at 405 nm over 30 mins on a spectrophotometer

(Biotek Cytation 5). In all cases, after averaging technical replicates, the linear region of the

reaction progress curve was determined by visual inspection and fit to a slope against the time of

progression. These slopes were then plotted against the corresponding concentrations of substrate

and fit to the Michaelis-Menten equation using non-linear regression to determine catalytic

parameters. Experiments were repeated at least three times across two batches of purified

proteins, and the average and standard error of the mean for all biological replicates are reported.

Cell culture

Normal breast epithelial MCF10A cells were grown in complete media: DMEM/50% F12 w/

GlutaMax (Invitrogen, 10565-018) supplemented with 5% Horse Serum (Invitrogen, 16050-

122), 0.02 μg/mL EGF (Peprotech, AF-100-15), 5 μg/mL Hydrocortisone (Sigma, H-0888), 10

mg/mL Insulin (Sigma, I-1882), 0.1 μg/mL Cholera toxin (Sigma, C-8052), and 1% Penicillin-

Streptomycin (Corning, 30-001-Cl). Cells were maintained in humidified incubators at 37°C

with 5% CO_2. MCF10A cells (ATCC: CRL-10317) were split at sub-confluency. Cells were

monitored for maintenance of epithelial morphology throughout experimental protocols. To

lower pHi, complete media was supplemented with 25 μM EIPA (Invitrogen, E3111) and 30 μM

S0859 (Sigma-Aldrich, SML0638-5MG). To raise pHi, complete media was supplemented with

30 mM ammonium chloride (NH₄Cl, Fisher Chemical, A661-500, Lot 185503). To inhibit SHP2,

complete media was supplemented with 15 µM PHPS1(Sigma-Aldrich, P0039) for 1 hour. To

inhibit EGFR, complete media was supplemented with 1 µM Erlotinib (BioVision, 1588-1000)

for 1 hour. To stimulate EGFR signaling, media was spiked with 10 ng/mL EGF (Preprotech,

AF-100-15-100UG) for 5 mins. All chemical concentrations are final concentrations (Cf).

pHi Manipulation and measurement

MCF10A cells were plated in 6 technical replicates for each treatment condition (6×100,000

cells/well; 24 well plate; 1 mL total volume). 24 hours after plating, media was exchanged with

pHi manipulation media. After 1 hour of incubation with pHi manipulation media, pHi was

measured as previously described(*61*). Briefly, 2′,7′-Bis-(2-Carboxyethyl)-5-(and-6)-

Carboxyfluorescein, Acetoxymethyl (BCECF-AM) Ester (Biotium, 51011) was added at 2 µM

(Cf) to cells for 30 min at 37°C with 5% CO_2. Cells were then washed 3x5 min with HEPES-

based wash buffer (30 mM HEPES, 145 mM NaCl, 5 mM KCl, 10 mM glucose, 1 mM KPO₄, 1

mM MgSO₄, and 2 mM CaCl₂) at 37°C. Wash buffers were supplemented with appropriate pH-

altering compounds at the same concentrations as the media. After washes, kinetic fluorescence

measurements were made at pH-sensitive wavelengths (490ex/535em) and the pH-insensitive

wavelengths (440ex/535em) every 15sec for 5 minutes at Medium PMT sensitivity on a plate

reader (Biotek Cytation 5). After the initial kinetic pHi read, wash buffers were removed and

replaced with the isotonic standardization buffer at ~7.5 pH (25 mM HEPES, 80 mM KCl, 1 mM

MgCl₂) supplemented with the protonophore nigericin (Invitrogen, N1495) at 10 µM (Cf). Cells

were incubated at 37°C for 10 min, and the plate was read again with the same parameters. The

high pH standardization buffer was then replaced with a ~7.0 pH nigericin buffer standard, cells

were incubated at 37°C for 10 min, and the plate was read again with the same parameters. The

nigericin buffer was then replaced with a ~6.5 pH nigericin buffer standard, cells were incubated

at 37°C for 10 min, and the plate was read again with the same parameters. Mean intensities

from pHi measurement and the nigericin standards were exported and pHi was back calculated

using a nigericin linear regression performed on each well with Nigericin standard pHi reported

to the hundredths place.

Western blotting

After pHi manipulation plates were removed from the incubator and placed on ice. The media

was aspirated, and the plates were washed two times with ice-cold DPBS. 200μL of lysis buffer

(500 mM NaCl, 10 mM EDTA, 500mM HEPES-free acid, 10 mM EGTA, 10% Triton X-100,

protease inhibitor cocktail (Pierce™ Protease Inhibitor Tablets, A32965; 1 tablet/50 mL lysis

buffer) and phosphatase inhibitor cocktail (PhosSTOP™, Sigma Aldrich, 4906845001), (pH 7.4)

was added to each plate. After 15 minutes of incubation in the lysis buffer, cells were removed

using cell scrapers and transferred to pre-chilled microfuge tubes. Lysates were centrifuged at

14,000 x g for 15 minutes at 4°C. Clarified lysates were isolated to separate microfuge tubes on

ice. The Bradford assay was used to quantify the total protein content of lysates (Bradford, 1976)

using Coomassie Protein reagent (Thermo Scientific, cat: 1856209). Lysates were stored at -

80°C if not immediately being used for SDS-PAGE sample preparation.

Protein samples were prepared in 6X Laemilli (reducing) buffer (Thermo Scientific, J61337-AC)

and boiled for 5 minutes at 100°C. A total of 10 μg of MCF10A lysate was added to each lane

for immunoblot analysis. Protein samples were loaded onto 12% SDS-PAGE gels, which were

run at 175V and 0.08 Amps for 15 minutes to stack samples. Protein samples were separated by

running the gel at 200 V and 0.08 Amps for an hour and a half. Polyvinylidene difluoride

(PVDF) membranes were pre-soaked in 100% methanol for 5 minutes and rinsed in turbo

transfer buffer. Transfers were performed at 1.00 A and 25V for 30 mins using the TransBlot

Turbo Transfer System (BioRad). Membranes were blocked for 1 hour in 5% milk (or 5% BSA

for phospho-proteins) in 1X Tris-buffered Saline + 0.1% Tween® 20 (TBS-T) at room

temperature with shaking. Membranes were washed 3x5 min in 1X TBS-T before being cut and

incubated with primary antibodies. The following primary antibodies were used: SHP2 (Cell

Signaling Technology, 3752; 1:1000 dilution in 1% milk in 1X TBS-T), pSHP2(Tyr524) (Cell

Signaling Technology, 3751T; 1:1000 dilution in 1% BSA in 1X TBS-T), Cofilin (Cell

Signaling Technology, 5175; 1:1000 dilution in 1% milk 1X TBS-T), HA (Cell Signaling

Technology, 3724; 1:1000 dilution in 1% milk 1X TBS-T), Actin (Santa Cruz, sc58673; 1:1000

diluted in 1% milk in 1X TBS-T), Src (Cell Signaling Technology, 2109; 1:1000 dilution in 1%

milk 1X TBS-T), pSrc(Tyr527) (Cell Signaling Technology, 2105; 1:1000 dilution in 1% BSA in

1X TBS-T), pSrc(Tyr416)(Cell Signaling Technology, 6943; 1:1000 dilution in 1% BSA in 1X

TBS-T), ERK (Santa Cruz, sc-514302; 1:1000 diluted in 1% milk in 1X TBS-T), pERK (Cell

Signaling Technology, 4370S; 1:1000 dilution in 1% BSA in 1X TBS-T), E-cadherin (Fisher

Scientific, 13-190-0; 1:1000 diluted in 1% milk in 1X TBS-T), pE-cadherin (ThermoFisher

Scientific, PA5-143661, 1:1000 diluted in 1% BSA in 1X TBS-T). Primary antibodies were

incubated overnight at 4°C with shaking. Primary antibody solutions were removed, and

membranes were washed 3x5 minutes in 1X TBS-T before incubating secondary antibodies

(Goat anti-mouse/rabbit HRP-conjugated antibodies; 1:10,000 diluted in 1% milk/BSA in 1X

TBS-T) for 1 hour at room temperature with shaking. Secondary antibody solutions were

removed, and membranes were washed 3x5 minutes in 1X TBS-T before being developed using

Pierce SuperSignal West Pico PLUS (Thermo Scientific, 34580) or Pierce SuperSignal West

Femto PLUS (Thermo Scientific, 34095). Chemiluminescence and colorimetric images were

acquired using a BioRad ChemiDoc imager.

Raw files were exported from ChemiDoc imager and opened in ImageJ. Band intensities were

acquired by densitometry analysis (area under the curve of individual bands in respective lanes).

For each replicate blot, target protein intensities were normalized to the intensity of loading

controls before normalizing each condition ratio to that of the control within biological

replicates.

Co-immunoprecipitation assays

After pHi manipulation plates were washed 2x with ice-cold PBS. The cells were then lysed on

ice. After Bradford measurements, 1µg of anti-SHP2 (Rabbit, Cell Signaling, 3752) was added to

100 µg of total lysate. The mixture was incubated on the rocker overnight at 4°C. Next, 80 µl of

protein A-dynabeads were added to each tube and the mixture was incubated on the rocker for 4

hours at 4°C. Next the beads were washed 3 times with 800 µl of wash buffer (TBS + 0.1%

Tween, EDTA-free Protease Inhibitor Cocktail (Roche, 04693132001)). After the final wash, the

beads were heated at 50°C in 50 µL of 2x Laemilli sample buffer (Biorad, 1610737) for 5

minutes to elute the proteins. Next the immunoprecipitation samples and total lysates were

immunoblotted. The following antibodies were used for primary incubations: SHP2(abcam,

ab76285; 1:1000 dilution in 1% milk in 1X TBS-T), GAB1 (Santa Cruz Biotechnology, sc-

133191, 1:1000 dilution in 1% milk in 1X TBS-T).

GRB2 TagBFP Assay: Live-cell Microscopy

The pHR Grb2-TagBFP plasmid, a gift from Jared Toettcher (Addgene plasmid # 188631

; http://n2t.net/addgene:188631 ; RRID:Addgene_188631)(*37*), was transfected into MCF10A

cells and grown for 24 hours before plating for experiments. The cells were plated on a 35mm

imaging dish with a 14mm glass coverslip (Matsunami, D35-14-1.5-U) a day before imaging.

Cell membranes were visualized via CellMask Deep Red (Thermo Fisher, C10046; 1:20,000),

incubated for 10 mins at 37°C in complete media. Microscope objectives were preheated to

37°C, and the stage-top incubator was preheated to 37°C and kept at 5% CO_2/95% air. Confocal

images were collected on a Nikon Ti-2 spinning disk confocal with a 60× (CFI PLAN FLUOR

NA 1.3) oil immersion objective. The microscope is equipped with a stage-top incubator (Tokai

Hit), a Yokogawa spinning disk confocal head (CSU-X1), four laser lines (405 nm, 488 nm, 561

nm and 647 nm), appropriate filter sets (BFP: 455/50; GFP: 525/36; Tx red: 605/52, and Cy5:

705/72), a Ti2-S-SE motorized stage, multi-point perfect focus system and an Orca Flash 4.0

CMOS camera. The cells were imaged initially for starting intensities before nigericin

stimulation. Next, the media was replaced with nigericin buffer (see **pHi manipulation and**

measurement section) to pin the cells at different pH values. The BFP (405 ex, 455/50 em;

500ms exposure) and Cell Mask (647ex, 705/72 em; 300ms exposure) for 15 mins at 30 second

intervals. The image quantification was performed in Nikon Elements software. Images were

background-subtracted using a region of interest (ROI) drawn on a glass coverslip (determined

by DIC). To only measure the intensity of the cell membrane, the ROI for membrane of each cell

was outlined using the membrane marker and tracked over time. In case of improper tracking

over time points, manual tracking was used to redraw ROIs.

Immunofluorescence assays

MCF10A Cells were plated in 35mm imaging dish with a 14mm glass coverslip
(Matsunami, D35-14-1.5-U) a day before treatment. The cells were then treated with pHi
manipulation drugs for an hour. Cells were rinsed with DPBS and fixed in 3.7% formaldehyde
(Alfa Aestar, 33314) at room temperature for 10 min. Cells were washed three times for 2 min
each time with DPBS, then incubated in lysis buffer (0.1% Triton-X in DPBS) for 10 min at
room temperature. Cells were washed three times for 2 min each time with DPBS, then
incubated in blocking buffer (1.0% BSA in DPBS) for 1 hour at room temperature with rocking
followed by three 2 min washes in DPBS. Cells were then incubated overnight at 4°C with anti-
C-Src antibody (Proteintech, 60315-1-Ig) and anti-pY416-C-Src antibody (ThermoFisher
Scientific, 44-660G). Cells were washed three times for 3 min each time in DPBS, then
incubated with secondary antibody and phalloidin for 1 hour at room temperature. After three 3
min washes in DPBS, Hoechst 33342 dye (1:20,000) in antibody buffer was added for 10 min,
then removed. Cells were imaged in DPBS on the spinning disk confocal microscope. Images
were collected in BFP (405 nm laser excitation, 455/50 nm emission, 200-500msec exposures);
GFP (488 nm laser excitation, 525/36 nm emission, 200-500msec exposures); Tx red (561 nm
laser excitation, 605/52 nm emission, 200-500msec exposures); and Cy5(647 nm laser excitation,
705/72 nm emission, 200-500msec exposures).

Constant pH molecular dynamics

The 2SHP and 2SRC monomer chains were downloaded from Protein Data Bank (PDB)
for initial structures. Constant pH MD (CpHMD) simulations were conducted following the
protocol described by Henderson *et al*., 2022(*34*). CpHMD simulations were performed with

implicit solvent using the GBNeck2-CpHMD method implemented in AMBER 2022(*62*).

Preparation of input files was done using the cphmd_pred.sh script provided in the protocol(*34*),

using the default titratable residue types (Asp, Glu, His, Cys, Lys). After energy minimization,

structure relaxation, and protonation state initiation(*34*), independent production simulations

were run over 4.0-10.0 pH in half-integer increments for 8 nanoseconds (ns) for each, resulting

in 13 independent CpHMD simulations and 104 ns of total simulation time for each structure.

Coordinate snapshots were saved every 20 picoseconds (ps), and protonation state snapshots

every 2 ps. The probability of protonated states became time-independent after 4 ns. The

resulting coordinate and protonation state trajectories were analyzed using Python scripts

provided in the protocol(*62*), the CPPTRAJ analysis program(*63*), and in-house Python scripts

(https://zenodo.org/records/15338058). To create the initial structure for the H116AE252A

mutant, we introduced the H116A and E252A mutations into the wild-type PDB (2SHP) using

the Mutagenesis Wizard functionality in Pymol Version 2.6. This mutant was simulated using

the same CpHMD protocol as for the WT protein.

Statistical analysis

GraphPad Prism was used to prepare graphs and perform statistical analyses. Normality tests

were performed on all data sets as well as outlier tests using the ROUT method (Q=1%).

Normally distributed data is shown with means and non-normally distributed data is shown with

medians. For normally distributed data, significance was determined by ratio paired t-tests or

appropriate ANOVA. For non-normally distributed data, significance was determined by

Kruskal-Wallis test. In all statistical tests, appropriate multiple comparisons corrections were

performed. "N" indicates the number of biological replicates performed and "n" represents the

number of technical replicates or individual cell measurements collected.

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The authors declare no competing interests.

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