

1 **Data and Text Mining**

2 **TransporterPAL: An integrative database Transporter Prediction ALgorithm**

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12 **Abstract**

13 **Motivation:** Natural products are used as drugs, cosmetic ingredients, pigments, flavors, and
14 agricultural products. The compounds are retrievable as extracts from natural sources, but the
15 yields are often low, and the final product may contain various impurities. These challenges can
16 be solved by expressing the biosynthetic pathway in microbial cell factories and ensuring
17 product secretion from the cell by using an appropriate transporter. However, insufficient
18 knowledge of transporters for specific compounds often obstructs efficient secretion of the
19 natural product. Therefore, our goal was to develop an algorithm that predicts transporters for a
20 given compound using available public data.

21 **Results:** The web application TransporterPAL predicts suitable transporters for compounds by
22 interconnecting data for biosynthetic genes and their interactions with transporters. The web
23 application queries the STITCH, STRING, and UniProtKB databases via their respective APIs

24 and returns a set of potential transporters based on a compound and, optionally, the organism as
25 input. For a test set of 61 transporter systems, each containing one or more transporters, a total of
26 90 unique transporters with a known substrate, we could retrieve 45% of the transporters. To our
27 knowledge, this is the first bioinformatics tool for predicting transporter candidates for a given
28 molecule.

29 **Availability:** <https://transporterpal.com>

30 **Contact:** irbo@biosustain.dtu.dk

31 **Supplementary information:** Supplementary data are available at Bioinformatics online.

32 **1 Introduction**

33 The demand for natural products is increasing in the pharmaceutical and biotechnological
34 industries. Due to the complexity of these molecules, the chemical synthesis of natural products is
35 usually challenging, if not impossible. Alternatively, natural products can be produced cheaper
36 and more sustainably by incorporating heterologous pathway genes into microbial cell factories.
37 Secretion of the synthesized molecules from microbial cells is vital to alleviate cellular toxicity,
38 prevent product degradation, and allow for high titer and purity (van der Hoek and Borodina,
39 2020). Often, a specific transmembrane transporter protein is required to engineer the secretion of
40 small molecules. However, transmembrane proteins are challenging to study, and many
41 transporters are thus not well characterized. As a result, the knowledge of appropriate transporters
42 is scarce, but the exploitation of data from several independent databases can provide clues about
43 potential transporters.

44 We hypothesized that if we can extract pathway genes for biosynthesis of a compound and other
45 proteins interacting with the compound, we can identify a suitable transporter among their
46 interaction partners in a functional association network. Furthermore, assuming the transporter is

47 present within this expanded set of proteins, we can use text mining to differentiate transporters
48 from other pathway proteins based on their functional description. Here, we present a web resource
49 that interacts with public databases to predict potential transporters automatically for a given
50 compound produced in nature, irrespective of protein annotation.

51 **2 Implementation**

52 STITCH (Szklarczyk *et al.*, 2016) is a database containing information about chemical–protein
53 interactions from many sources, including biological pathway databases, automatic text mining of
54 biomedical literature, and experimental data repositories. The STRING database (Szklarczyk *et*
55 *al.*, 2021) similarly provides physical and functional protein–protein interactions integrated from
56 various sources. Finally, UniProtKB (Bateman *et al.*, 2021) provides functional annotations of
57 proteins, including Gene Ontology (GO) annotations related to transport activity.

58 Our workflow consists of the following steps, starting from a chemical and, optionally, an
59 organism of interest: (i) use chemical–protein interactions from STITCH to obtain an initial set of
60 proteins (Szklarczyk *et al.*, 2016), (ii) expand this set of proteins with their interaction partners
61 using functional associations from STRING (Szklarczyk *et al.*, 2021), (iii) select the transport-
62 related proteins from this set based on UniProtKB GO annotations (Figure 1). To combine the
63 information from all these databases, we access them via their respective REST APIs. Specifically,
64 we use the *interactors* API method of STITCH to obtain interacting proteins with the input
65 chemical, then the *interaction_partners* API method of STRING to expand the set of proteins. We
66 convert the STRING identifiers to UniProt IDs using the UniProt Retrieve/ID mapping service and
67 subsequently retrieve the UniProtKB record for each ID via the UniProt API. Each record contains
68 information about the protein, and as we search specifically for transporters, we filter the records
69 based on keywords related to transport activity. We have used UniProt GO annotations for cellular

70 components, molecular functions, and biological processes to generate a list of transporter-related
71 keywords. After removing protein entries unrelated to transport, the UniProtKB accession number,
72 protein name, and organism name are retrieved from UniProtKB. The interaction between the
73 compound and each putative transporter is scored using the combined score from the network
74 STITCH API, as described in (Szklarczyk *et al.*, 2016).

75 The web application is based on Python3 and uses STITCH, STRING, and UniProt APIs. We use
76 the python packages requests, csv, json and sys. Furthermore, asyncio and aiohttp are used to make
77 asynchronous API calls. The web application has been developed using an Express NodeJS web
78 application framework in combination with the basic web application building blocks, HTML,
79 CSS, and Javascript.

80 **3 Availability**

81
82 On the online server <https://transporterpal.com>, the user enters a natural compound and, optionally,
83 an organism. A link to available organisms is provided on the website. When the web application
84 has finished, it sends an email containing a CSV file and a FASTA file containing the amino acid
85 sequences of the identified transporters.

86

87 **4 Current benchmarking**

88 Although the algorithm works with any organism, we tested the algorithm on a data set of bacterial
89 transporters extracted from the Transporter Classification Database (Saier *et al.*, 2021), a database
90 containing experimentally verified transporters, to quantify the number of transporters we can
91 retrieve by using the algorithm. We chose transporters of degradation pathways and secondary

92 metabolite biosynthesis produced by specific bacteria and corroborated their pathway in MetaCyc
93 (Caspi *et al.*, 2020). We selected transporters from 61 transporter classification IDs, each
94 containing one or more transporters, in total 95 transporters (Supplementary data). A few of the
95 transporters mediate transport of more than one compound, which makes 90 of the transporters
96 unique. Of the unique transporters, 35 were not present in the databases; For 20 compounds,
97 transporters related to a specific organism were unavailable in STITCH, primarily due to
98 unrepresented species. Additional nine transporters were not present in the STRING database.
99 Furthermore, six transporters did not have a link between the STRING and UniProtKB databases.
100 From the remaining data set of 55 proteins, 14 transporters were not found either because they
101 were not among the interaction partner proteins or because they did not contain the transporter-
102 related GO-annotation keywords. Ultimately, 41 proteins were correctly retrieved, corresponding
103 to 46% of the 90 unique transporters. The predictive power of TransporterPAL depends on
104 available data, highlighting the need for more experimental research on transporter function
105 characterization.

106

107 **5 Conclusion**

108 We have developed a web application to predict potential transporters based on the pathway genes
109 and interacting proteins of a given compound and organism. With more research on transporters
110 and the addition of knowledge into the STITCH, STRING, and UniProtKB databases, we expect
111 to increase the success rate of retrieving suitable proteins with transport activity for a specific
112 compound. While we focus on transporters, this method is easily extendable to study other
113 pathway proteins by changing the filters in the GO annotation to keywords suitable for a particular

114 protein family class. To our knowledge, this is the first tool able to link potential transporters to a
115 given natural product.

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121 **Conflict of Interest:**

122 None declared.

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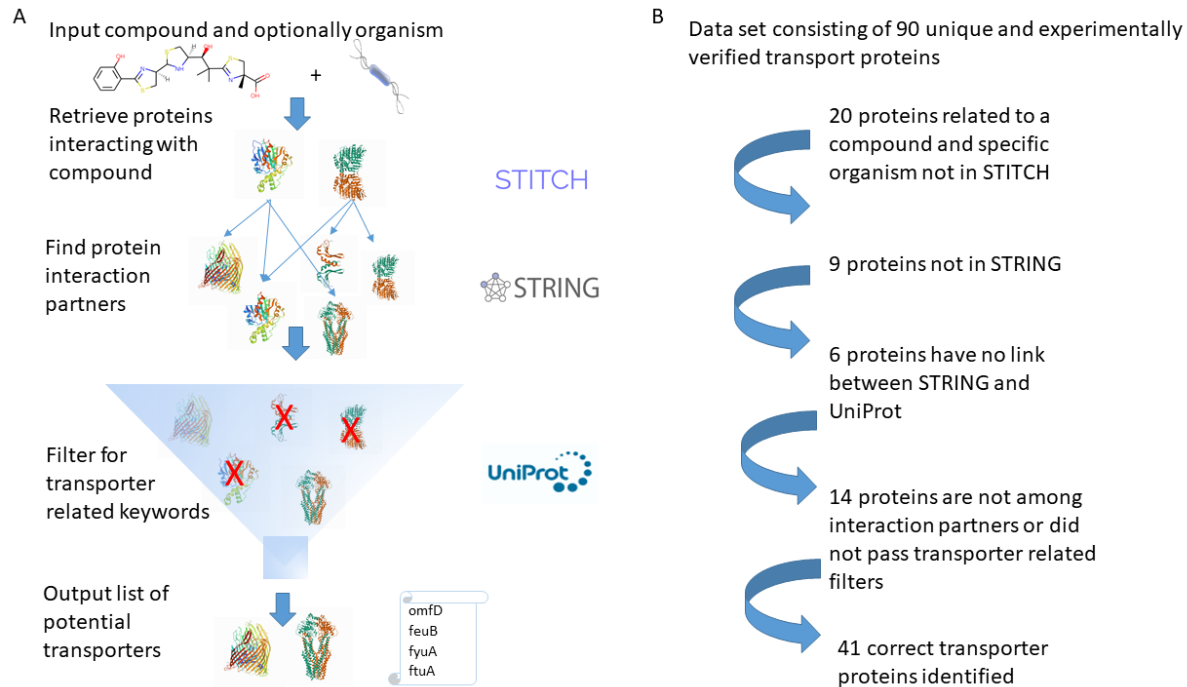
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139 Figure 1. TransporterPAL workflow for transporter identification. Panel A. We use the STITCH
140 database to extract pathway genes and proteins interacting with the compound for an organism.
141 This set of proteins is expanded by their interaction partners using STRING. The list contains
142 non-transporter-related proteins, and we exclude these by filtering for transporter-related GO
143 annotations using UniProt to obtain a final list of potential transporters for the compound. Panel
144 B. 90 unique, experimentally verified transporter proteins were used in the test set. Twenty
145 proteins related to a compound and specific organism were unavailable in STITCH. Nine
146 proteins were not present in the STRING, and six transporters did not have a link between the
147 STRING and UniProt databases. In the remaining data set of 55 transporters, 14 were not found,
148 resulting in 41 correctly identified transporter proteins.