Metabolomic characterization of behaviorally manipulated ants with multiomic data integration

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Abstract

10   Parasitically manipulated *Camponotus floridanus* ants show multiple diseased behaviors and a

fatal summiting phenotype when infected by *Ophiocordyceps camponoti-floridani* fungi. Altered host

behavior as a response to and driven by parasites occur in a broad swath of taxa. In many cases, such as

this interaction, the underlying mechanisms have not yet been clearly characterized. The drastic

phenotypic changes observed could in some cases reflect large physiological changes within cells,

spanning different molecular levels from nucleic acids to metabolites. Here, we link existing genomic and

transcriptomic data to a new metabolomic dataset we produced to hypothesize on the mechanisms of

manipulated "zombie ants" from a multiomic perspective. Multiple lines of evidence point toward

dysregulation of neurotransmitters and neuronal signaling. We propose that these processes are altered

during infection and manipulation based on: neurotransmitter synthesis and receptor gene expression,

altered metabolite abundances, with plausible behavioral ties to known effects of these neurotransmitters

in ants and other insects, and possible suppression of a connected immunity pathway. We additionally

report signals for fungal metabolic activity during manipulation and early evidence for alterations of host

processes related to detoxification, anti-stress protectants, and insect hormone metabolism.

Introduction

Hosts infected by parasites can show altered phenotypes that can be adaptive for the host or parasite. In the latter case, specifically promoted parasite-adaptive changes in host behavior are often referred to as parasitic behavioral manipulation. Examples of apparent manipulations of host behavior and physiology occur in a broad range of host and parasite taxa, although the underlying mechanisms are still being revealed (Thomas *et al.* 2010; Moore 2013; Heil 2016; Libersat *et al.* 2018; de Bekker *et al.* 2021).

In many parasitic manipulations, insect hosts succumb to summit disease, where the manipulated individual occupies an elevated location and dies in a stereotypical manner (Lovett *et al.* 2020; de Bekker *et al.* 2021). These final, elevated, exposed summit positions can be adaptive for the parasite by aiding transmission either by direct dispersal of the parasite or trophic transmission. As an example of the summit and disperse strategy, the ant-manipulating *Ophiocordyceps* (zombie ant fungi) have been leveraged in laboratory studies to better understand the mechanistic basis of behavioral manipulation. Manipulated ants display a summiting behavior, latching and biting onto their final summit perches until their death. Preceding this fatal change in behavior, infected ants also deviate from foraging trails and increase locomotor activity, reduce nestmate communication, and convulse (Pontoppidan *et al.* 2009; Andersen *et al.* 2009; Hughes *et al.* 2011; de Bekker *et al.* 2015; Sakolrak *et al.* 2018; Trinh *et al.* 2021).

Observed manipulation phenotypes likely do not hinge solely on activity by only the host or parasite. Rather, ant hosts may already demonstrate behaviors that can be easily coopted for manipulation by the fungal parasite. In this case, the parasite may benefit by taking advantage of and influencing host processes and symptoms without relying on costly mechanisms to "rewire" their hosts (Adamo 2019; Lovett *et al.* 2020). Although, deeper understanding of the fitness cost and benefits for both hosts and parasites may reveal that such behaviors could also be sometimes adaptive for hosts, at the individual or group level (perhaps especially so for eusocial animals, such as ants). Regardless of the ultimate "source" of manipulated behavior, physiological and molecular characterizations of hosts displaying modified behavior may offer a glimpse into how parasites (or hosts) modulate animal behavior, the coevolution of specialized host-parasite relationships, and undescribed properties of certain proteins and metabolites.

In the myrmecophilous *Ophiocordyceps*, investigations of phenotypes, genomes, transcriptomes,

and metabolomes continue to accumulate and help bring the most robust mechanistic hypotheses into

focus. The range of hypotheses touch upon: neuromodulators and effector proteins, circadian rhythms and

phototropism, insect hormones and behavioral-profile regulators, neuroprotectants, and muscular

hyperactivity (de Bekker *et al.* 2014a; Kobmoo *et al.* 2018; de Bekker 2019; Mangold *et al.* 2019; Zheng

et al. 2019; Loreto and Hughes 2019; Will *et al.* 2020; Trinh *et al.* 2021; de Bekker and Das 2022).

Previous metabolomic works centered on the *Ophiocordyceps kimflemingiae* zombie ant fungus have

already identified various metabolites associated with manipulation. These metabolomic signals also vary

in a species-specific manner, changing when either the parasite or host was a exchanged for a different

species (de Bekker *et al.* 2014b; Zheng *et al.* 2019; Loreto and Hughes 2019). Here, we continue to add to

these works in a "multiomic" approach with a new metabolomic analysis of *Camponotus floridanus*

(Florida carpenter ant) manipulated by *Ophiocordyceps camponoti-floridani* (Florida zombie ant fungus)

interpreted in the context of existing transcriptomic and genomic data (Will *et al.* 2020).

As the key processes of manipulation could involve specialized and general mechanisms, host

and parasite effectors, or changes from the genetic to chemical level, multiomic approaches cast a broad

net to improve detection. At the same time, combing these multiple approaches and datatypes can identify

consistent and robust signals for key biological processes. To supplement existing transcriptomic data, we

collected metabolomic data using three liquid chromatography-tandem mass spectrometry (LC-MS/MS)

protocols. We focused on altered metabolic pathways supported by a combination of metabolite and gene

signals. Similarly, we note when manipulation-associated metabolite features are selected by multiple

statistical methods. This approach follows the intuition that every analysis is subject to its own biases but

data that represent substantial biological changes are more likely to be selected by multiple

complementary tests.

Our study compared whole head samples of healthy *C. floridanus* ants and ants manipulated by

O. camponoti-floridani. Sampling whole heads allowed direct comparison to Will *et al.* 2020

transcriptomic ant-head data. Although metabolomic signals will be homogenized, whole heads will

contain the chemical profiles of ant neural tissue, muscle, and hemolymph in addition to fungal cells that

all may contain metabolites of most interest (Hughes *et al.* 2011; de Bekker *et al.* 2014b, 2015;

Fredericksen *et al.* 2017; Mangold *et al.* 2019; Zheng *et al.* 2019; Loreto and Hughes 2019). By analyzing

our metabolomic data in light of previous genomic and transcriptomic data, we propose multiple

pathways and compounds that reflect, or drive, manipulated behavior in *Ophiocordyceps* infected ants.

Results & discussion

Infection mortality, observations of manipulation, and LC-MS/MS datasets: Similar to

previous laboratory infections with *O. camponoti-floridani* (Will *et al.* 2020), *C. floridani* displaying

manipulated biting in this study were collected between 4 hr before to 0.5 hr after dawn, beginning three

weeks after infection (Fig. 1). Sham treatment healthy ants showed no mortality until 29 days post

injection (dpi), whereas infection treatment ants began to die immediately once we started recording

deaths on 4 dpi. This difference in survival was markedly different between treatments (p = 4.1E-7, log-

rank test) (Fig. 1A). In total, three sham treatment ants died out of the 28 (11%) that survived through 3

dpi. Twenty-three infected ants were manipulated out of the 39 (59%) that survived through 3 dpi. The

other 16 infected ants died with visible blastospore loads but without observed behavioral manipulation.

In total, these experimental infections produced 20 manipulated ants, 20 healthy (sham) ants, and

three blank-collection samples produced from the ant housing of the sham treatment (Fig. 2A). From

these samples, we produced three LC-MS/MS datasets, "biogenic amines," "polyphenols," and "lipids,"

containing 2,955, 4,315, and 4,924 analyzed features, respectively. (Fig. 2A-B).

Figure 1. Ant manipulations occur at stereotypical days and times.

A) *O. camponoti-floridani* infection leads to significantly increased mortality compared to sham treatment (p = 4.1E-7, log-rank test). B) Manipulated ants most often appeared 21-27 dpi, but as late as 33 dpi. C) Manipulated ants were collected near dawn, most often at ZT 21.5, 2.5 hr before lights turned on.

Metabolomic feature selection and grouping for pathway enrichment analyses: After data quality control and filtering (Fig. 2B), we constructed a set of features for study-wide pathway enrichment analysis that distinguished healthy and manipulated ants by: categorization as differentially abundant metabolites (DAMs), loading values in principal component analyses (PCAs), and importance for navigating decision trees (Boruta) (Kursa and Rudnicki 2010) (Fig. 2C). Combining all three LC-MS/MS datasets, approximately 60% of features were DAMs, with most DAMs increasing in abundance in manipulated ants compared to healthy controls (Fig. 3A, Table 5). Separation of treatment groups by PCA only clearly clustered along PC1 (ca. 60% to 80%), with PC2 (ca. 4% to 9%) and other PCs (not shown) describing little of the variation between treatments (Fig. 3B). Using Boruta random forests, we found ca. 40% of features to be "confirmed" as "important" for distinguishing treatment types (Table 5). We performed pathway analyses with a study-wide group of features that satisfied at least

117   **Figure 2. Experimental overview and analytical framework for enrichment analyses.**

A) Three types of experimental samples were collected, blank-collections (mock sampling using tools and ant housing for healthy ants), healthy ants (given sham-injections only), and manipulated ants (infected with *Ophiocordyceps* and displaying manipulation phenotypes). The metabolomics core facility introduced two quality control (QC) extractions. First, blank-extractions using core facility materials only (and therefore distinct from experimental blank-collections). Second, pooled extractions of all samples used for a given LC-MS/MS dataset. Three LC-MS/MS datasets were produced, each being an untargeted analysis but tailored to different chemistries to collect broad data overall. B) The metabolomics core generated "Processed data" from which we produced "QC filtered data" and "Analyzed data" by applying quality control and data reduction steps. C) We used multiple statistical tests to select features of interest for metabolic pathway enrichment analyses. Results from those enrichment analyses were subsequently subjected to multiple filters to arrive at a final set of pathways and feature sets of interest. Full details on these samples and approaches are given in Methods.

two of following criteria: (*i*) it was a DAM, (*ii*) it was among the highest 50% of absolute PC1 loading values, or (*iii*) it was confirmed by Boruta. Most features that satisfied at least two requirements (n = 6,468 features, 53% of a total 12,194 features), in fact satisfied all three (n = 4,656, 72% of features passing two criteria) (Fig. 2C, 15C, Supp. Table 1, Supp. Data 1). The feature set passing at least two filters contained 347 of the 760 (46%) features given compound annotations by the WCMC. The many features passing our filters is likely due to a combination of metabolites related specifically to infection processes and general aspects of fungal metabolism, as *O. camponti-floridani* cells were only present in manipulated ants. For this set of features passing at least two selection filters, we jointly analyzed them with Mummichog and a gene set enrichment analysis (GSEA)-based approach in MetaboAnalyst for enriched metabolic pathways found in the Kyoto Encyclopedia of Genes and Genomes (KEGG) (Fig. 2C) (Kanehisa and Goto 2000; Li *et al.* 2013; Pang *et al.* 2021). We detected eight significantly enriched pathways that passed our p-value, minimum metabolite feature, fold-enrichment, and enzyme differentially expressed gene (DEG) thresholds (Fig. 2C, Table 6, Supp. Data 2). These enzyme DEGs use previously published expression data from an *Ophiocordyceps* manipulation study (Will *et al.* 2020) and were associated here with their respective KEGG metabolic pathways. Most enzyme DEGs were downregulated both in the ant (90%) and the fungus (62%). This degree of downregulation is higher than previously found for transcriptome-wide DEGs during manipulation (Will *et al.* 2020) (Supp. File 1).

Figure 3. Feature selection overview.

A) Volcano plots per dataset show DAMs that increased (red) or decreased (blue) at manipulation according to a 1.5-

fold change and p ≤ 0.05. B) PCAs for each dataset show distinct clustering of samples between manipulated (orange)

and healthy ants (gray) along PC1. C) Features that passed at least two selection criteria (bold) were used for study-

wide pathway analyses. We used DAM analyses to select features as described above, PCAs to select features in the

top 50% of PC 1 loading values, and the Boruta analysis to select features identified as "important."

Table 1. All enriched KEGG pathways selected across analyzed feature sets.

KEGG pathways that were found in Mummichog or GSEA analyses (p ≤ 0.05) also were required to show a

minimum 1.25-fold enrichment, three features contributing to that enrichment, and three DEGs that were

homologous to representative enzyme genes within that pathway. Each pathway is listed alphabetically once in the

table, with all feature sets (network modules or the study-wide feature set that passed at least two selection filters)

that were enriched for that pathway.

Enriched KEGG metabolic pathway	Feature sets				
Alanine, aspartate and glutamate metabolism	P13				
Amino sugar and nucleotide sugar metabolism	A1	P1	P2	P3	P18	study-wide
Aminoacyl-tRNA biosynthesis	L3	P2	P11		
Arginine and proline metabolism	A1	P2			
Arginine biosynthesis	A1				
Ascorbate and aldarate metabolism	A1	P13			
beta-Alanine metabolism	P2	study-wide			
Biosynthesis of unsaturated fatty acids	L2	L10	P3	study-wide	
Butanoate metabolism	P2				
Citrate cycle (TCA cycle)	P3	P13			
Cyanoamino acid metabolism	A1				
Cysteine and methionine metabolism	L1	P1	P18		
Drug metabolism - cytochrome P450	L3	P3			
Drug metabolism - other enzymes	A1	study-wide			
Fatty acid degradation	P3				
Folate biosynthesis	P2				
Fructose and mannose metabolism	P2	P18			
Galactose metabolism	A1	P18	study-wide		
Glutathione metabolism	A1				
Glycerolipid metabolism	P2				
Glycerophospholipid metabolism	P2	study-wide			
Glycine, serine and threonine metabolism	P2	P11			
Glycolysis or Gluconeogenesis	P3				
Glyoxylate and dicarboxylate metabolism	P13				
Histidine metabolism	A1				

Inositol phosphate metabolism	P2				
Insect hormone biosynthesis	A1	P3			
Lysine biosynthesis	A1				
Lysine degradation	P2				
Metabolism of xenobiotics by cytochrome P450	A1	P2			
Nicotinate and nicotinamide metabolism	P2				
Pantothenate and CoA biosynthesis	A1	P18			
Pentose and glucuronate interconversions	A1	P18			
Pentose phosphate pathway	A1	L1	P1	P2	P3	P18
Phenylalanine metabolism	A1	P2			
Purine metabolism	L1	P1	P18		
Pyrimidine metabolism	A1	P11	study-wide		
Pyruvate metabolism	P13				
Starch and sucrose metabolism	A1	P3	P18		
Sulfur metabolism	P2				
Taurine and hypotaurine metabolism	L1	P1			
Tyrosine metabolism	P2	P3			
Ubiquinone and other terpenoid-quinone biosynthesis	P3				
Valine, leucine and isoleucine degradation	P18	study-wide			

Many metabolite features in our dataset were uniquely represented in manipulated samples: 454

features were never detected in healthy sham treatment ants and 1,781 additional features either were

detected in less than 50% of the healthy ants and/or their median peak value was not at least double that

of blank-collection controls (2,235 features total). These features may represent compounds tightly

regulated and scarce in the healthy ant or uniquely produced by the fungus. We predicted that this feature

set might have been enriched for hallmarks of infection and manipulation processes. However, no

significant pathway enrichments were returned from our Mummichog and GSEA analyses. This could

indicate that these metabolites are not linked by common metabolic pathways and/or many of these

metabolites were not well annotated in the KEGG databases (e.g., species-specific metabolites).

We used a weighted gene co-expression network analysis (WGNCA) based approach to cluster

metabolite features that similarly change abundance levels between healthy and manipulated *C.*

floridanus treatments (Fig. 2C) (Langfelder and Horvath 2008). Co-expression (or co-abundance)

networks, in some cases, suggest linked biological functions and activity in the same metabolic processes

(Stuart *et al.* 2003; Carlson *et al.* 2006; Gillis and Pavlidis 2012; Bartzis *et al.* 2017). We detected three

biogenic amine, eight polyphenol, and five lipid network modules that were significantly correlated to

treatment (Fig. 4). A total of six biogenic amine (A1-A6), 19 polyphenol (P1-P19), and 10 lipid (L1-L10)

networks were created in total. Due to our sparse annotation

Figure 4. WGCNA network modules of metabolite features and their correlation to manipulation.

In total we detected three, five, and eight significantly correlated (Student correlation ≥ |0.5|, p ≤ 0.05, denoted with

*) network modules to manipulation in the biogenic amines, lipids, and polyphenol datasets, respectively. Network

modules were constructed as unsigned, meaning the direction of the correlation describes the network as a whole,

although some features may be anti-correlated within the module. "Unsorted" modules contain all features that were

not successfully correlated to other features in a network (i.e., by default labeled "gray" by R package WGCNA).

data, we were not able to consistently compare hub features. As such, we considered all available

annotations within a network module and Mummichog pathway enrichments (Fig. 2C). Across all

network modules significantly correlated to the transition from healthy to manipulated ants, 44 unique

enriched KEGG pathways were selected, which included the eight found across the study-wide data that

passed at least two selection filters (Table 6, Supp. Data 2).

The biogenic monoamine neurotransmitters dopamine, serotonin, and octopamine are

known to modulate ant activity and may be proximate drivers of diseased behaviors: A combination

of pathway enrichments, annotated DAMs, and DEGs suggest that shifts in metabolism associated with

neurotransmitters relate to behavioral alterations in *C. floridanus* infected and manipulated by *O.*

camponoti-floridani. The monoamine neurotransmitters dopamine, serotonin, and octopamine (analogous

to vertebrate norepinephrine) have been implicated in modulating locomotor, foraging, learning, social,

reproductive, and aggressive behaviors in many insects, and have been tested in social insects, including

ants (Adamo 2008; Aonuma and Watanabe 2012; Adamo *et al.* 2013; Kamhi *et al.* 2017; Verlinden

2018). Serotonin, octopamine, and melanin derived from L-3,4-dihydroxyphenylalanine (L-DOPA), or

tyrosine and dopamine, have roles in insect immunity as well (Geun *et al.* 2009; González-Santoyo and

Córdoba-Aguilar 2012). Administration of dopamine and serotonin to *Formica polyctena* wood ants or

Odontomachus kuroiwae trap-jaw ants have produced altered behaviors in the laboratory, such as

aggressive mandible-opening or biting behaviors and defensive responses (Szczuka *et al.* 2013; Aonuma

2020). In the field, *Pogonomyrmex barbatus* harvester ant dopamine levels positively correlated with

foraging trips, as seen both by dopamine supplementation and inhibition (Friedman *et al.* 2018).

Similarly, pharmacological depletion of serotonin led to reduced and impaired trail-following foraging

behavior in *Pheidole dentata* ants (Muscedere *et al.* 2012). In *Formica aquilonia*, there is evidence for

octopamine increasing aggressive behaviors (Yakovlev 2018), however, clear signs of increased

aggression with octopamine treatment was not found in *F. polyctena* (Szczuka *et al.* 2013). Octopamine

additionally appears to modulate the social behavior of trophallaxis in *Camponotus fellah*, while serotonin

had no significant effect (Boulay *et al.* 2000). As such, the exact effects of these neurotransmitters can

differ by species and social or physiological context. However, many of these affected behaviors are

relatable to the disease phenotypes observed in *Ophicordyceps* infected ants. Observations of

Ophiocordyceps-infected ants include changes in behavior leading to increased walking, deviation from

foraging trails, reduced nestmate communication, and the final manipulated bite (Pontoppidan *et al.* 2009;

Andersen *et al.* 2009; Hughes *et al.* 2011; de Bekker *et al.* 2015; Trinh *et al.* 2021).

Furthermore, gene expression networks negatively correlated between the ant and fungus were

enriched for host neuronal function and parasite manipulation-associated secreted proteins. This

correlation suggested parasite effectors promote, directly or indirectly, the downregulation of host gene

modules related to neuronal maintenance, circadian rhythm, olfaction, and memory (Will *et al.* 2020).

Additionally, direct host-parasite interactions have been hypothesized to occur by fungal proteins binding

ant neuroreceptors for dopamine, serotonin, and octopamine (Will *et al.* 2022 preprint). Although we did

not directly identify dopamine, serotonin, or octopamine in our metabolomic data, we did measure

features annotated as biosynthetically related compounds.

Changes in dopamine metabolism possibly modified ant behaviors and shifted host-pathogen

immunological interactions during manipulation. A combination of metabolomic and transcriptomic data

indirectly suggest increased dopamine metabolism in manipulated ants. The metabolomic signals

consisted of changes in neurotransmitter precursor abundances and enrichment of pathways in metabolite

network modules correlated to manipulation. Phenylalanine and tyrosine are precursors in synthesis

pathways for dopamine and octopamine. KEGG pathway "phenylalanine metabolism" was enriched in

both network modules A1 and P2 ($p = 0.026$ and 0.028, fold-enrichment = 1.5 and 1.9, respectively), both

of which were negatively correlated to manipulated ant samples. Additionally, KEGG pathway "tyrosine

metabolism" was enriched in modules P2 and P3 ($p = 0.030$ and 0.024, fold-enrichment = 1.4 and 1.6,

respectively), both also negatively correlated to manipulation. Moreover, module P2 also contained the

most informative compound annotations regarding dopamine metabolism.

The immediate precursor to dopamine, L-DOPA, was 2.8-fold reduced in abundance in

manipulated ants ($p = 0.008$, and in the top-50% of PC1) (Fig. 5). L-tyrosine was also annotated in

Figure 5. Altered neurotransmitter precursor metabolism suggests suppressed ant immunity, increased dopamine and serotonin, and reduced octopamine during infection and manipulation.

Cardol triene may produced by the fungus to suppress ant immunity and thereby also increase availability of tyrosine and L-DOPA for dopamine synthesis. L-amino acid decarboxylase (AADC) catalyzes the final step of dopamine and serotonin synthesis and is upregulated by manipulated ants. A reduction of L-DOPA and tryptophan suggest that these compounds are being converted into dopamine and serotonin, respectively. Upregulation of an ant kynurenine aminotransferase possibly increases or maintains (if the kynurenine precursor is reduced) kynurenic acid levels. The possible of reduction of octopamine concentration follows the reasoning that it requires L-tyrosine for its synthesis, which is reduced during manipulation, and there is no compensatory upregulation of enzyme genes in the octopamine pathway to compete with upregulated dopamine biosynthesis. Dysregulated ant behavior during infection and manipulation may arise due to this altered neurotransmitter metabolism. Network modules from which

discussed feature annotations or enriched pathways reside are given at the bottom of the figure. Increases are

indicated by solid lines and red color, decreases by dotted lines and blue color, metabolites are in rounded

rectangles, genes are in rectangles, annotated metabolites that were not DAMs have gray color, compounds with

white color were not identified in the LC-MS/MS data, and hypothesized functional links are given in the shaded

circles. Metabolic steps that did not have DEG are shown as black arrows when useful for context but are omitted

elsewhere. A squiggled arrow indicates metabolite interaction with a receptor. Tryptophan is given colored as a

reduced abundance DAM, but was selected rather by the Boruta analysis only and not the differential abundance t-

test.

module P2 and is the precursor to L-DOPA and tyramine. The latter can be converted into the

neurotransmitter octopamine. L-Tyrosine was a DAM with a 2.1-fold decrease in abundance (p = 1E-4,

and Boruta confirmed). An annotation for tyrosine was also present in the network module A1, however,

we did not identify this metabolite feature as a DAM (p = 0.154, 1.2-fold reduction). Outside of network

modules A1, P2, and P3, we also detected phenylalanine, the precursor to tyrosine. Phenylalanine showed

a modest increase in abundance during manipulation just below our 1.5-fold change threshold for

classification as a DAM (p = 0.019, 1.4-fold increase) (Fig. 5). Decreases in L-tyrosine and L-DOPA

could be difficult to interpret alone, however in combination with RNAseq data, we found evidence for

increased dopamine synthesis that offers one explanation for the depletion of these dopamine precursors.

During manipulation, both ant hosts and fungal parasites upregulated an aromatic L-amino acid

decarboxylase (AADC) gene (Fig. 5). This enzyme catalyzes the final step of L-DOPA conversion to

dopamine and the conversion of L-5-hydroxytryptophan to serotonin (Dakshinamurti *et al.* 2017). The

AADC enzyme requires vitamin B6 as a cofactor and we detected differential abundance of an inactive

vitamer form and a precursor for *de novo* synthesis in module A5 (Supp. File 2). However, the

combination of metabolomic and transcriptomic data available do not provide for a clear interpretation for

if active vitamin B6 is changing in abundance and in which organism(s).

A tyrosine 3-monooxygenase, which catalyzes the rate-limiting conversion of L-tyrosine to L-

DOPA, was upregulated by manipulated ants. Meanwhile, the ant homolog to Henna (i.e., DTPHu

phenylalanine 4-monooxygenase), which converts phenylalanine to L-tyrosine was not differentially

expressed. This enzyme also converts peripheral tryptophan to the serotonin precursor in *D. melanogaster*

(Neckameyer and White 1992; Coleman and Neckameyer 2005; Neckameyer *et al.* 2007). This consistent

expression may help explain the only modest change of phenylalanine during manipulation while its

derivatives were found at lower concentrations.

Dopamine and its precursors can also be converted into melanin, a key compound for insect

wound response and immunity (González-Santoyo and Córdoba-Aguilar 2012; Sugumaran and Barek

2016; Wang *et al.* 2017). Fungi can also synthesize melanin for use in host-pathogen interactions and

against competing microbes (Nosanchuk and Casadevall 2006; Nosanchuk *et al.* 2015). We found

evidence that this pathway for melanin production is reduced in the ant during manipulation and,

possibly, increased in the fungus (Fig. 5).

We propose that the production of a fungal-derived compound may inhibit tyrosinases necessary

to convert dopamine-pathway metabolites to melanin and hence simultaneously steer these metabolites

toward dopamine production. This metabolite feature was annotated as cardol triene (i.e., 5-(8,11,14-

pentadecatrienyl)resorcinol) and was a DAM only detected in manipulated ant samples (p = 0.0073,

median peak value = 19,604, in the top 50% of PC1) (Fig. 5). As cardol triene was never detected in

healthy ants, it plausibly is produced solely by the fungus, although we cannot discount the possibility

that production of this metabolite is produced by ants combatting infection and completely absent in

healthy individuals. We detected the putative cardol triene in six of 10 manipulation samples, this could

indicate that cardol triene levels are tightly regulated. Cardol triene has been shown to inhibit tyrosinase

oxidation of L-DOPA (Zhuang *et al.* 2010). In insects, phenoloxidases are a type of tyrosinase and are

key enzymes that begin the conversion of dopamine and L-DOPA to pro-immune melanin production

pathways (Gorman and Arakane 2010; González-Santoyo and Córdoba-Aguilar 2012; Wang *et al.* 2017).

As such, we hypothesize that fungal cardol triene chemically inhibits host phenoloxidase activity to

reduce melanin metabolism.

Additionally, ants showed mixed transcriptional signals related to the melanin-immune response

by phenoloxidase and phenoloxidase activating factor genes (Fig. 5) (Piao *et al.* 2005). Entomopathogen

infections suppress phenoloxidase activity in mosquitoes and the inhibition of activation of pro-

phenoloxidase has been hypothesized as a mechanism of fungal interference with insect host immunity

(Feng *et al.* 2015; Ramirez *et al.* 2018). In addition to suppressing host melanin production, the fungus

may be converting L-DOPA or related compounds into fungal melanin precursors, as four upregulated

and one downregulated tyrosinases were found during manipulation (Fig. 5). Three of the upregulated

fungal tyrosinases are putatively secreted and may possibly interact with host tyrosine and its derivatives.

The sum result of this proposed altered dopamine metabolism could weaken host immunity, bolster

parasite pathogenicity, and drive altered host behavior by increased dopamine concentration (Fig. 5).

Serotonin and octopamine metabolism may also correlate to manipulated ant behavior.

Biosynthetically and phenotypically intertwined with dopamine, fluctuating serotonin and octopamine

concentrations may contribute to manipulated ant behavior. Although the metabolomic signals for these

compounds were less robust than for dopamine, we found multiomic evidence that offers support for

hypotheses of increasing serotonin and decreasing octopamine (Supp. File 3). For example, upregulation

of the AADC enzyme shared between dopamine and serotonin pathways and at least one signal for the

reduction of tryptophan (selected by Boruta), which can be converted into the precursor for serotonin.

Coupled with the increasing serotonin, we additionally propose a hypothesis for increased kynueric acid,

which is also tied to tryptophan and may act as a neuroprotectant for heavily diseased and manipulated

ants (Supp. File 3).

Multiomic synthesis of transcriptomic and metabolomic data. Our hypotheses link enzyme gene

transcription and metabolite precursor abundance to predict an increase of dopamine with a reduction in

host melanin and immunity. Using similar reasoning, but with less robust metabolomic support, we

consider increases of serotonin and kynurenic acid, while octopamine may be reduced (Supp. File 3). An

alternative interpretation of the data could be that increased gene expression does not indicate elevated,

functional protein abundance in every case, and may even be a homeostatic response to low enzyme

activity or substrate abundance. However, without new proteomic data, we suggest that inferring protein

levels by transcription to generally be the most parsimonious explanation. Similarly, reduced precursor

abundances could reflect wide-spread reduced levels of metabolites, including neurotransmitter products.

But in the context of the observed behavioral manipulation phenotypes and reconciling transcriptomic and

metabolomic data, we propose a set of hypotheses we deem most plausible. Regardless of whether each

neurotransmitter discussed is increased or decreased in abundance, our data link changes in

neuromodulatory processes and parasitically manipulated behavior.

Altered glycerophospholipid metabolism suggested increased fungal cell membrane activity

and ant accumulation of the excitatory neurotransmitter, acetylcholine: The KEGG pathway

"glycerophospholipid metabolism" was enriched in module P2 and in study-wide features passing at least

two selection filters ($p = 0.024$ and 0.030, fold-enrichment $= 1.9$ and 1.4, respectively). We found

evidence for two possible major effects, changes in cell membrane composition and the accumulation of

acetylcholine. Of our annotated features, metabolic signals centered on choline offered the most insight

into altered glycerophospholipid metabolism. Glycerophospholipids and choline-containing compounds

have been associated with neurodegenerative disease, such as Alzheimer's or Parkinson's, and insect

host-pathogen responses (Walter *et al.* 2004; Hoxmeier *et al.* 2015; Alecu and Bennett 2019). Choline is a

key component involved in the synthesis of phospholipids associated with forming cell membranes,

especially as incorporated through phosphatidylcholine (Li and Vance 2008). Although, in fungi and

insects, phosphatidylethanolamine is also a major cell membrane component (Batrakov *et al.* 2001;

Dawaliby *et al.* 2016; Cassilly and Reynolds 2018). Using the lipids LC-MS/MS dataset we compared

peak values of phosphatidylethanolamines (n = 95 features) and phosphatidylcholines (n = 85 features)

and found phosphatidylethanolamines to indeed be abundant in our insect and fungal tissue samples.

Within healthy ants, phosphatidylethanolamines were only slightly more abundant (1.10-fold greater)

than phosphatidylcholines (t-test, $p = 0.017$, $t = -2.657$). Within fungus-manipulated ants, there was no

strong difference (t-test, $p = 0.739$, $t = -0.339$, phosphatidylethanolamines 1.05-fold higher). As both

phospholipid types were nearly equally abundant, we considered changes of metabolites of either class

could reflect important processes during manipulation.

Feature sets: enriched pathways and annotated metabolites

study-wide — Glycerophospholipid metabolism / ethanolamine phosphate

P2

P18 — glycerophosphocholine

A5 — choline / acetylcholine / ethanolamine

Figure 6. Changing glycerophospholipid metabolism during manipulation primarily indicate altered acetylcholine levels in the ant and cell membrane metabolism in the fungus.
Manipulated ant samples appeared to have two distinct groups, one with high acetylcholine and one with levels similar to healthy ants. In manipulated ants, the putative acetylcholinesterase and two acetylcholine receptor genes were downregulated, suggesting acetylcholine levels were accumulating. We hypothesize that increased acetylcholine in manipulated ants is associated with the increased muscular activity during early manipulation (e.g., tremors, biting, and latching behavior). Once the ant is secured in a summited position and the mandible muscles (and associated neurons) are further degraded, the fungus may be scavenging and converting the available acetylcholine to choline, thereby rapidly reducing acetylcholine levels. The fungus may be converting choline to

phospholipids, such as phosphatidylcholine to remodel and build cell membranes. Although we did detect multiple

features in the class of phosphatidylcholines and phosphatidylethanolamines, we did not identify the singular

metabolites "phosphatidylcholine" and "phosphatidylethanolamine" themselves. Network modules from which

discussed feature annotations or enriched pathways reside are given at the bottom of the figure. Increases are

indicated by solid lines and red color, decreases by dotted lines and blue color, metabolites are in rounded

rectangles, genes are in rectangles, annotated metabolites or genes that were not DAMs or DEGs have gray color,

compounds with white color were not identified in the LC-MS/MS data, and hypothesized functional links are given

in the shaded circles. Metabolic steps that did not have DEG are shown as black arrows when useful for context but

are omitted elsewhere. A squiggled arrow indicates metabolite interaction with a receptor.

Choline was a DAM increasing during manipulation ($p = 1.7E-11$, 20.0-fold increase, passing all

selection criteria) (Fig. 6). We also observed other DAMs related to choline within the

glycerophospholipid metabolism pathway. Glycerophosphocholine, a choline precursor was increased at

manipulation and detected in two datasets ($p = 3.4E-11$ and $1.2E-7$, 5.9- and 7.7-fold increase, passing all

three selection criteria). We also detected two DAMs interconnected between choline and

phosphatidylethanolamine: ethanolamine ($p = 5.2E-5$, 2.1-fold increase, also Boruta confirmed) and

ethanolamine phosphate ($p = 1.6E-9$, 5.5-fold decrease, passing all selection criteria) (Fig. 6). Three

putative *Ophiocordyceps* phospholipase C genes were DEGs, two upregulated and one downregulated

(Fig. 6). Broadly, phospholipid C proteins cleave phospholipids and have been implicated in cell

signaling, pathogenicity, and cell membrane metabolism (Pokotylo *et al.* 2013). When cleaving either

phosphatidylcholine or phosphatidylethanolamine they can produce an intermediate 1,2-diacyl-sn-

glycerol product. Additionally, the fungus expressed a putative diacylglycerol cholinephosphotransferase

gene 1.9-fold higher during manipulation, nearly qualifying as a DEG. This enzyme combines 1,2-diacyl-

sn-glycerol and CDP-choline to produce phosphatidylcholine. Phosphatidylcholine could then be

converted to glycerophosphocholine within two metabolic steps, but this pathway appeared to be

downregulated. Three genes putatively encoding the enzymes driving this conversion were downregulated

in the ant (phospholipases A1, A2, and B). In the fungus, a phospholipase B-like gene was also

downregulated (Fig. 6). The net effect appears to be fungal composition and/or catabolism of

phosphatidylethanolamines and synthesis of phosphatidylcholines leading to a minor compositional shift

overall during manipulation - but perhaps including specific and important changes we cannot yet identify

(Fig. 6). Modification of the cell membrane could be necessary to accommodate transmembrane proteins

or secretory activity involving organelle membranes such as in the endoplasmic reticulum (van der Veen

et al. 2017; Shyu *et al.* 2019).

Choline can also be metabolized into acetylcholine, the most abundant excitatory

neurotransmitter in insects (Gauthier 2010). In bees, excessive activation of acetylcholine receptors can

cause changes in locomotor, navigational, foraging, and social behaviors (Grünewald and Siefert 2019).

Acetylcholine can be rapidly converted back to choline by the activity of the acetylcholinesterase enzyme,

which has been a target of enzyme-inhibiting insecticides (Quinn 1987; Fournier *et al.* 1992; Colovic *et*

al. 2013; Singh *et al.* 2017). From this fast enzymatic activity, we intuit that acetylcholine levels could

reflect changes in physiology and behavior at a fine timescale. A subgroup of the manipulated ant

samples showed markedly higher acetylcholine levels than both healthy and other manipulated ants (Fig.

6). As such, we propose a scenario of transiently increased acetylcholine during manipulation, only

detected in a subset of our samples.

Acetylcholine showed a 2.7-fold mean increase at manipulation overall, but was not identified as

a DAM (p = 0.142), with a feature-peak value distribution showing two distinct groups. Three

manipulated ants had 5.5-fold higher acetylcholine peak values than the other seven that spanned a similar

range as control samples (Fig. 6). Speculatively, this could indicate that, for some fast-changing

metabolites such as acetylcholine, our sampling approach captured multiple subtly different physiological

states during the dynamic process of behavioral manipulation. The previously collected transcriptomics

data similarly showed the broadest distribution of acetylcholinesterase-2 expression during manipulation.

In the ant, an acetylcholinesterase-2-like gene was downregulated during active manipulation overall, but

two of the five samples had 2.5-fold lower acetylcholinesterase expression than the other three (Supp. Fig.

1) (Will *et al.* 2020). As the ant dies, acetylcholinesterase-2 expression begins to rebound toward healthy

ant levels. Notably, acetylcholinesterase-2 is the functionally dominant acetylcholinesterase enzyme in

Camponotus and many hymenopterans (Kim and Lee 2013). Additionally, the ant downregulated a

putative muscarinic acetylcholine receptor gar 2 that has been found in sensory and motor neurons of *C.*

elegans (Lee *et al.* 2000). Nearly a DEG as well, a putative ant nicotinic acetylcholine receptor acr-16

subunit gene was expressed 1.9-fold lower during manipulation. Possibly, receptor downregulation

represents a homeostatic response to the proposed elevated acetylcholine levels present during part of

manipulated summiting and biting.

Although acetylcholine has fast-acting regulatory effects on motor behavior, importantly,

glutamate is the direct primary excitatory neurotransmitter at insect neuromuscular junctions (Johansen *et*

al. 1989; Gauthier 2010; Pflüger and Duch 2011). Glutamate was nearly classified as a reduced DAM (p

= 0.007, 1.4-fold decrease) while a related compound, glutamine, did qualify (p = 1.8E-6 and 6.2E-11,

3.3- and 3.8-fold decrease, in network module A5 and also P2, respectively), with transcriptomic

evidence that suggested the host and parasite may be mounting contrasting regulatory responses (Will *et*

al. 2020) (Supp. File 4).

Common metabolites between *Ophiocordyceps*-*Camponotus* manipulations in two species

pairings: Previous metabolomic studies with *O. kimflemingiae* have identified many metabolites

associated with infection of *C. castaneus* and proposed links between these compounds and manipulation

(de Bekker *et al.* 2014b; Zheng *et al.* 2019; Loreto and Hughes 2019). Laboratory co-culture of *O.*

kimflemingiae with brains from *C. castaneus* and other ant species showed shared metabolites and distinct

compounds reflecting a combination of target host-specific fungal secretions and ant species profile (de

Bekker *et al.* 2014b). Other studies have compared *O. kimflemingiae* infections to that by a generalist

entomopathogenic fungus, again finding both overlap and differences in metabolomic profiles (Zheng *et*

al. 2019; Loreto and Hughes 2019).

Ergothioneine, an amino acid produced by some fungi, but not animals, has been detected in

mixed ant-fungal tissue from manipulated ant brains and muscles (Zheng *et al.* 2019; Loreto and Hughes

2019). Corroborating these findings, we detected two ergothioneine signals (biogenic amine and

polyphenol datasets) that were wholly absent in the healthy ants or with peak values near that of blank-

collection samples (p = 7.3E-15 and 4.6E-12, passing all selection criteria). In addition to fungal

metabolism, ergothioneine has been discussed as a possible neuroprotectant to preserve the ant brain until

manipulated summiting and biting are complete (Loreto and Hughes 2019). Supporting this line of

reasoning, ergothioneine in the ant brain was not detected at elevated levels in moribund ants infected by

the generalist entomopathogen *Cordyceps bassiana* that consumes hosts more quickly, without inducing

summit disease, and appears to occupy the ant head capsule to a lesser extent than *Ophiocordyceps*

(Fredericksen *et al.* 2017; Loreto and Hughes 2019).

Previous work with *O. kimflemingiae* and this work with *O. camponoti-floridani* have found

adenosine and adenosine-phosphate (AMP) to be differentially abundant between manipulation and

healthy and/or generalist-infected ants (Zheng *et al.* 2019; Loreto and Hughes 2019). We found two

features annotated as adenosine, one which was not differentially abundant and one that was a reduced

DAM in manipulated samples (p = 6.6E-4, 2.5-fold decrease). In contrast, previous works found

adenosine to increase in abundance in both manipulated ant brains and mandible muscles (Zheng *et al.*

2019; Loreto and Hughes 2019). Whether these contrasting results indicate species-specific patterns or

high variation is unclear. We also found decreased AMP (p = 0.003, 2.1-decrease, Boruta confirmed) in

the head, as was found in manipulated *C. castaneus* (Zheng *et al.* 2019; Loreto and Hughes 2019). In *O.*

kimflemingiae infection, a role for adenosine mediated neuromodulation was hypothesized, as was

changing AMP levels possibly reflecting changes in mitochondrial activity (Zheng *et al.* 2019; Loreto and

Hughes 2019). Cyclic AMP is involved in many pathways, including as a secondary messenger in G-

protein coupled receptor signaling, which includes receptors for dopamine and other neurotransmitters,

and have been hypothesized to be implicated in manipulation based on gene expression and host-parasite

protein-protein interaction predictions (Will *et al.* 2020, 2022 preprint). If changing abundance of AMP

reflects upon the cyclic form as well, this could relate to dysregulation of receptor signaling.

Metabolically related to adenosine, hypoxanthine and inosine were also proposed to have links to

energetic and neurological processes in manipulated ants (Zheng *et al.* 2019; Loreto and Hughes 2019).

As in those studies, we also detected increased levels of hypoxanthine during manipulation, two of three

features annotated as hypoxanthine increased at manipulation (p = 0.007 and 7.7E-6, 1.6-fold increase or

absent in sham, the latter of which passed all selection criteria). We also detected one inosine and two

inosine-monophosphate features increased in manipulated ants (p = 0.002, 3.8E-7, and 1.4E-5, 1.9-, 2.8-,

2.5-fold increase, all Boruta confirmed). This could indicate the conversion of AMP and adenosine to

hypoxanthine primarily via inosine intermediates.

Pathways and compounds with reduced multiomic support: Metabolomics results without

robust multiomic support or clearly annotated metabolite features provide a basis for future investigations.

Pathway enrichments without high-confidence metabolite annotations suggested possible changes in

insect hormone and detoxification metabolism during manipulation (Supp. File 5). With supporting

metabolite annotations but lacking strong genomic or transcriptomic evidence, we speculate that the

fungus may synthesize a cytoprotectant (carnosine), which could be derived from host compounds and

protect key host tissues (e.g., brain) during infection (Supp. File 5).

Conclusion

Infection and behavioral manipulation of hosts could involve many interacting molecular and

cellular processes. As these host-parasite interactions are better characterized, we can also gain insights

into specialist co-evolutions, the mechanistic basis of animal behavior, and the discovery of new bioactive

compounds. To unravel the mechanistic complexity of infection and manipulated host behavior, we

require functional tests built upon robust hypotheses. Towards this goal, we studied parasitic

manipulation of *C. floridanus* by *O. camponoti-floridani*, combining metabolomic, transcriptomic, and

genomic data to develop a set of hypotheses regarding molecular processes during manipulation.

We found evidence for altered biogenic monoamine neurotransmitter production during infection

and manipulation that may be proximate causes of manipulated behavior. In total, we propose a scenario

where the manipulated ant has elevated production of dopamine, with possible increases of serotonin and

decreases of octopamine. The fungus may also simultaneously suppress the host's melanin and immunity

pathways while metabolizing dopamine and its precursors for fungal melanin production. Ants infected

by *Ophiocordyceps* display enhanced locomotion/activity levels, reduction of social behaviors, and a final

summit latching behavior – elements of these behaviors have already been associated with

neurotransmitter signaling in ants. Intriguingly, aquatic gammarid crustaceans manipulated by

acanthocephalan worms display a phototactic summiting and clinging phenotype in the water column

sometimes associated with increased serotonin, decreased octopamine, and suppressed phenoloxidase-

mediated immunity – essentially, parts of the same pattern we propose in manipulated *Camponotus*

(Helluy and Holmes 1990; Lefèvre *et al.* 2009; Helluy 2013; Herbison 2017). Manipulators of vertebrate

behavior may also leverage serotoninergic and dopaminergic processes to alter fish and mouse behaviors

related to escape responses, locomotion, and aggression (Shaw *et al.* 2009; Prandovszky *et al.* 2011;

Adamo *et al.* 2013; Lafferty and Shaw 2013). How much of the alteration of neurotransmitter metabolism

may be a general response to fungal infection and how much results from specific manipulation by

Ophiocordyceps is difficult to pinpoint at this time. However, cardol triene appears to be a fungal derived

compound that could suppress ant immunity and increase substrate availability for dopamine production.

Also, *Ophiocordyceps* upregulated three putatively secreted tyrosinases that possibly interact with host

dopamine/melanin precursors. Although less typically reported than their intracellular counterparts,

extracellular fungal tyrosinases have also been found in another fungus (Selinheimo *et al.* 2006;

Gasparetti *et al.* 2012). Dopamine, serotonin, and octopamine receptors appear to be directly targeted by

secreted fungal effector proteins as well (Will *et al.* 2022 preprint). Given the importance this may place

on a functional host brain and body, indications in our data for altered neuro/cyto-protectant

concentrations and detoxification metabolism may indeed reflect key changes in the manipulated

metabolome. Although, further evidence is required to fully assess this.

Changing glycerophospholipid metabolism during manipulation, largely centered on choline,

suggested fungal biosynthesis of cell membrane components and dysregulation of acetylcholine levels in

the ant. *Ophiocordyceps* may require increased choline-derived cell-membrane components used during

cell proliferation and membrane remodeling for structures such as lipid rafts or transmembrane proteins

important during infection and manipulation. Manipulated ants reduced expression of

acetylcholinesterase, and three metabolomic manipulation samples had notably higher acetylcholine

concentrations than the rest. Speculatively, transient high acetylcholine could contribute to summiting and

wandering behavior (i.e., increased locomotion), tremors, and the hypercontracted biting that locks

manipulated ants into place.

By inducing changes in neurotransmitters that regulate behavior in healthy ants, the fungus may

be impinging upon existing host systems to modify behavior rather than forcibly introducing novel

pathways. Indeed, many of the hallmark phenotypes of infection by ant-manipulating *Ophiocordyceps* are

not so dissimilar from activities influenced by levels of dopamine, serotonin, octopamine, and

acetylcholine in eusocial insects: foraging/locomotor behavior (i.e., summiting and hyperactivity),

sociality (i.e., wandering and reduced communication), and the biting/aggression (the final "death grip"

bite). Changes in social behavior could not only be a symptom of disease, but contribute to it as well. As

socially isolated infected ants may less frequently exchange trophallactic fluid with nestmates, these

infected individuals would lose an important source of nutrition, communication, and hormones (Leboeuf

et al. 2016) that may alter their metabolome. How exactly the fungus dysregulates physiological pathways

that influence behavior (e.g., juvenile hormone metabolism) and to what degree some level of

dysregulation is typical in many diseases is still unclear. These hypotheses can be further investigated by

functional tests (e.g., gene knockouts or dosing ants with metabolites) and LC-MS/MS validations of key

compounds using chemical standards.

Methods

Ant collection & husbandry: We used a single laboratory-housed wild-caught colony of *C.*

floridanus to produce all samples. This colony was collected in March 2021 in the University of Central

Florida arboretum. This colony had several hundred individuals including minors, majors, and brood.

Based on methods in Will *et al.* 2020, we housed the colony in a plastic container within a climate-

controlled incubator (I36VL, Percival) cycling 12 h-12 h, light-dark, 28 C°-20 C°, 65% RH-80% RH

daily cycles. Climate conditions cycled in a ramping manner, with a 4 h ramp from lights-on to a 4 h hold

at peak day conditions to a 4 h ramp to lights-off (additional husbandry details in Supp. File 6).

Fungal strain OJ2.1 collection, culture, and storage: *O. camponoti-floridani* strain OJ2.1 was

used to infect all ants in this work. We isolated this fungal strain using mycelium extracted from the

abdomen of a fresh, manipulated *C. floridanus* cadaver. This cadaver was found in the Ocala National

Forest, FL (29° 13' 41.7" N, 81° 41' 44.9" W). The isolation procedure, short ribosomal subunit genetic

validation, and culturing followed the protocols detailed in Will *et al.* 2020. In preparation for

experimental infections, we grew fungal cells for 10 days in liquid shaking cultures with Grace's medium

(Gibco) supplemented to 2.5% fetal bovine serum (Gibco) ("GF" medium). We then filtered (two-layers

of 12-ply gauze, Curity) and adjusted the blastospore cells to a working concentration of approximately 3

x 10^6 cells/mL (optical density 660 nm = ca. 0.5) prior to injection.

We have not incorporated isolated *in vitro* fungal control samples as was done for transcriptomic

analysis in Will *et al.* 2020. Such samples would not likely have been effective and efficient to include

given the higher number of samples required for robust LC-MS/MS analysis, fungal metabolite

production can be highly reflective of culture conditions (VanderMolen *et al.* 2013), and, unlike

transcriptomic analyses, we would not be able to discern the origin of metabolites in mixed-organism

manipulated ant samples regardless. Instead, we used the transcriptomic data to propose links of altered

metabolite abundances during manipulation to either the host or parasite.

Experimental infections of ants: Ten days before infection, we separated ants from their colony

into boxes per treatment group. For the *Ophiocordyceps*-infection treatment, we gathered 41 ants and 10

additional caretaker ants with painted abdomens (Testors paint), which did not receive the treatment but

assisted the 41 injected ants with recovery. One day before infection treatments, we removed the sugar

and water from the ant box to reduce the amount of fluid in the ants and ease the injection procedure. Due

to a husbandry accident that led to widespread death of the initial sham-infection treatment ants, we

repeated the sham treatment two weeks after the *Ophiocordyceps* experimental treatment. Ants from the

same colony were used for the sham treatment (n = 30 with 8 painted caretakers) and were maintained in

the same incubator as all other ants.

Ants were either anesthetized by placing their plastic box on top of ice prior to injection, or

directly injected at room temperature. We injected each ant with 0.5 µL *Ophiocordyceps* blastospores

(infection, n = 41) or 0.5 µL of GF (sham, n = 30) as detailed in Will *et al.* 2020. We placed the treated

ants and their painted caretaker ants in plaster-lined boxes with biting structures (*Tillandsia usneoides* tied

to wooden sticks with twine) and returned them to the climate-controlled incubator.

Observation and sample collection for LC-MS/MS: After 3 dpi we removed dead ants. Then,

we began screening for manipulated ants and deaths twice per day, at zeitgeber-time (ZT)-0, the

beginning of subjective day, and ZT-6, the mid-point of subjective day. At 10 dpi, we removed the

painted caretaker ants as previous work has observed *C. floridanus* to destroy and interfere with

manipulated nestmates, presumably as a component of their social immunity and nest hygiene (Diez *et al.*

2014; Will *et al.* 2020; Trinh *et al.* 2021). Starting 15 dpi, we began more frequent opportunistic checks

as behavioral manipulations of *C. floridanus* had been observed starting 19 dpi in the laboratory (Will *et*

al. 2020). After discovering the first manipulation at 21 dpi, we made multiple daily checks beginning at

ZT-20 and ending at ZT-14 (on the next subjective day). Previous laboratory *O. camponoti-floridani*

manipulations synchronized to the ants' subjective pre-dawn hours and we selected our observation times

to improve the odds of collecting manipulations close to their beginning (Will *et al.* 2020). We screened

non-manipulated mortalities for fungal infection by crushing tissue from the dead ant in 50 µL of water,

briefly touchdown centrifuging, and examining 15 µL of the supernatant on a microscope. Notable levels

of fungal cells were always and only seen in the *Ophiocordyceps* treatment ants. We analyzed and plotted

survival data using the R packages survival and survminer in R (v 4.1) with R Studio (v. 2021.09.2)

(RStudio Team 2015; Therneau 2015; Kassambara *et al.* 2019; R Core Team 2021).

LC-MS/MS samples. We collected live manipulated ants displaying characteristic summiting

biting behavior for LC-MS/MS immediately upon discovery (n = 20) (Fig. 2A). We subsequently

collected dpi-matched sham ants at ZT-21.5, as this was the most common time at which manipulated

ants were collected (n = 20) (see Results and Discussion, Fig. 2A). Manipulated ants found after death

were recorded for survival statistics but not used in the LC-MS/MS analyses (n = 3). For manipulated ant

collection, we clipped the biting substrate just above and below the manipulated ant and submerged the

ant in liquid nitrogen briefly until frozen. The sample was then placed in a pre-chilled, sterile 2 mL

microcentrifuge tube (USA Scientific) kept in liquid nitrogen until long-term storage at -80 C°. We

collected sham ant samples in a similar manner, plucked from the experiment box with forceps.

We created three blank-collection samples at the beginning, middle, and end of manipulated ant

sampling, i.e., after the first, 10th, and 20th manipulated ants were found (n = 3) (Fig. 2A). We made

blank-collection samples by briefly touching the forceps to the floor of the sham treatment housing boxes,

submerging them in liquid nitrogen, and swirling them in a microcentrifuge tube. We cleaned all tools and

surfaces with 70% ethanol and deionized water before sampling and between sample types.

We later prepared collected samples for LC-MS/MS by isolating ant heads. Each frozen ant was

quickly processed on a plastic petri dish (USA Scientific) on a bed of dry ice. Using forceps, we removed

biting substrate from the ant's mandibles if needed, snapped the head off, and placed it in a new

microcentrifuge tube. Heads were paired together by collection date into 10 two-head pools per treatment,

but later separated for analysis (see below). For blank-collection samples, we dragged the forceps along

the petri dish and swirled the forceps inside the original collection tube. We cleaned the tools and petri

dish with 70% ethanol and deionized water between individuals and used a new petri dish between

sample types. All samples and tubes were kept constantly chilled on dry ice or in liquid nitrogen.

LC-MS/MS processing of ant head samples: All samples were sent on dry ice to the West

Coast Metabolomics Center (WCMC, University of California, Davis) for LC-MS/MS analysis. The

WCMC processed samples in three LC-MS/MS protocols broadly tailored toward different chemistries:

"biogenic amines," "polyphenols and flavonoids," and "complex lipids." From the 20 samples collected

per infection and sham treatments, the WCMC collected polyphenol data for 10 individual ant heads, one

from each two-head pool. They used the remaining ten heads per treatment for biphasic extractions, with

each individual head used for both biogenic amines and lipids (Fig. 2A). Blank-collection samples were

shared across the three LC-MS/MS chemistries. The WCMC produced quality-control (QC) pool samples

consisting of all samples used per protocol and additional blank-extraction controls (Fig. 2A). These

WCMC control samples were run at the beginning and every ten samples thereafter per protocol. All LC-

MS/MS protocols collected MS/MS data in a top-four data-dependent-acquisition (DDA) mode in both

electrospray ionization (ESI) positive and negative modes.

632   The WCMC processed samples for biogenic amines for use in hydrophilic interaction

633   chromatography (HILIC) with quadrapole time of flight (Q-TOF) mass spectrometry. Homogenized ant

634   head samples were extracted with a methanol and methyl-tert-butyl ether protocol (Matyash *et al.* 2008)

635   and the aqueous phase used for biogenic amines LC-MS/MS and the organic phase used for lipids (see

636   below). Extractions were mixed with internal standards for normalization according to WCMC protocols

637   to a final volume of 100 μL (Supp. Data 3). Further details are provided in Supp. File 7.

638   Samples for lipids were processed for use in charged surface hybrid (CSH) chromatography with

639   Q-TOF mass spectrometry. The organic phase per biphasic extraction (shared with biogenic amines, see

640   above) was taken for lipids LC-MS/MS and mixed with internal standards according to WCMC protocols

641   (Supp. Data 3) to a final resuspension volume of 110 μL. Further details are provided in Supp. File 7.

642   Samples for polyphenols were processed for use in pentafluorophenyl (PFP) chromatography

643   with QExactive HF (QE) mass spectrometry. Homogenized ant head samples were extracted in a similar

644   fashion as described above and resuspended in a final 100 μL volume with internal standards (Supp. Data

645   3). Further details are provided in Supp. File 7.

646   **Metabolomic data processing & feature filtering:** The WCMC performed initial processing

steps on all samples to produce metabolomic feature lists consisting of mass/charge ratio (*m/z*), retention

time (rt), and value of quantification ion peaks. They aligned raw data with MS-DIAL (v 4.7.0) (Tsugawa

et al. 2015), subtracted signals detected in the blank-extractions produced in the core facility, removed

duplicate signals and isotopes, normalized samples by internal standards, and assigned compound and

adduct annotations based on manual MS/MS matching in Massbank, Metlin, and NIST14 databases and,

for lipids, with LipidBlast (v 68) (Kind *et al.* 2013) (Fig. 2B). The resulting data consisted of several

thousand features per dataset: biogenic amines (5605 total with 141 annotated), polyphenols (6178 total

with 158 annotated), and lipids (7021 with 517 annotated) (Supp. Data 4).

We applied additional feature quality control and data reduction methods to create a final list of

metabolite features to investigate. Features that had greater than 50% missing values within both sham

and infection treatments were removed. Similarly, we removed features with both median peak values

(sham and infection) less than double that of median blank-collection peaks. Following removal based on

missingness and peak values, we removed features that we determined to have signals too variable for

robust analysis based on their coefficient of variation (CV%, or relative standard deviation) (Fig. 2B). For

the biogenic amines and lipid datasets that had successful QC pool data returned, we applied a CV%

maximum threshold to remove peaks that varied greatly due to technical variation between QC pool

injections. We selected the CV% threshold as the lowest (i.e., strictest) value between 30% and a dataset

specific value determined from the distribution of CV% values. We calculated this data-specific value as

the 75th-quartile + 1.5*interquartile-range (IQR), as is used to identify extreme values or outliers in data

distributions (e.g., boxplots). For the lipids, the 1.5*IQR method produced CV 25% as the cutoff,

removing 5.7% of features. For biogenic amines, the 1.5*IQR CV% was greater than 30%; therefore,

30% was used, removing 6.6% of features. The WCMC reported that all polyphenol QC pools failed on

acquisition. Therefore, we ranked each feature by its lowest CV% (i.e., from either CV%-sham or CV%-

manipulated) and removed the highest 6.1% of features. We selected this 6.1% value because it was the

mean of the CV% removal rates of the biogenic amine and lipid datasets. Although we cannot fully

discount biological variation in biogenic amine peak values within a treatment, by selecting the lowest

CV% per feature (whether from the sham or infection treatment), we sought to remove only features that

had high CV% regardless of treatment. After all these filtering steps, we continued with 3268 biogenic

amine features (58% of initially collected), 4878 polyphenol features (79% of initial), and 6305 lipid

features (90% of initial).

We further applied a putative adduct calling step to consolidate unannotated features that may

represent different adducts of the same compound. Per LC-MS/MS dataset, we divided features by

treatment and ESI mode, and processed each of these subsets with Binner (v 1.0.0) (Kachman *et al.* 2020)

(Fig. 2B). Briefly, Binner compares metabolite features "binned" by rt and calls putative adduct

relationships between these features based on a table of possible adducts, feature *m/z*, and correlation of

peak values across samples. Data were split by treatment to avoid possibly conflating signals for different

compounds found in only one of the treatments as adducts of each other. Data were natural log

transformed, no additional deisotoping step was preformed, the mass tolerance was set to 0.005 Da

(biogenic amines and lipids) or 0.003 Da (polyphenols), and default settings were used elsewhere. For

biogenic amines and polyphenols, we searched for adducts used in KACHMAN *et al.* 2020. For lipids, we

supplemented this adduct table with an additional adduct set publicly available online (Fiehn Lab 2020).

We then reunited data subsets to create feature lists that included all peaks that were labeled as primary

ions or remained unannotated in either treatment group. In effect, this step only removed peaks that were

determined to be putative adduct peaks in both treatments, resulting in the final processed datasets for

analysis of: 2955 biogenic amines (90% of QC filtered peaks remained), 4315 polyphenols (88% of QC

filtered peaks), and 4924 lipids (78% of QC filtered peaks) (Supp. Data 1).

Metabolomic data analysis & feature selection: To select a single set of study-wide features of

interest combined across all three datasets, we applied three statistical approaches (Fig. 2C). For features

with values equal to zero, we imputed zeros as 20% of the minimum value measured for that feature.

Each analysis we preformed was done independently per LC-MS/MS dataset (biogenic amines, lipids,

and polyphenols). We determined if a feature represented a DAM with a t-test (corrected FDR, $p \leq 0.05$)

and minimum ±1.5-fold change in abundance between sham and infection treatments. Principal

component analyses always indicated that only PC1 separated samples by treatment type (see Results). As

such, we noted features ranked in the upper 50% of PC1 absolute loading values. Given that our choice of

threshold was defined as half of the data, we did not rely on this test solely as merit for discussing a

feature, but rather as a way to add confidence to results of other analyses. Both t-tests and PCAs were

performed through the MetaboAnalyst interface (v 5.0) (Pang *et al.* 2021). Finally, we selected features

"confirmed" as "important" by Boruta (v 7.0.0, R package) random-forest based analyses with 900

maxRuns and 70,000 ntree settings (Kursa and Rudnicki 2010). In brief, "important" features are selected

by z-scores of mean decrease accuracy in decision trees in comparison to randomized versions of the data

(Kursa and Rudnicki 2010). Boruta offers an improvement over standard random-forest analyses for high

dimensional data such as in metabolomics, increasing the stability and robustness of the features selected

(Acharjee *et al.* 2020).

Additionally, we created co-abundance network modules of metabolite features per LC-MS/MS

dataset using the WGCNA method (Langfelder and Horvath 2008) (Fig. 2C). Although the WGCNA was

developed primarily for gene expression data, this technique has been used and evaluated for

metabolomic data as well (Bartzis *et al.* 2017). Heightened activity in a metabolic pathway could lead to

many compounds increasing. But simultaneously, their precursors may become depleted. Therefore,

correlations within a network could be both positive and negative. As such, we constructed unsigned

WGCNA modules. All WGCNA modules were constructed on feature data without imputing zeros, based

on the biweight midcorrelation to compare between treatment types (e.g., corFnc="bicor", robustY=F,

maxPOutlier=0.05) (R package WGCNA, v 1.67). In cases where zeros were present, the analysis

defaulted to the Pearson correlation for that feature. We obtained similar network modules when the

Pearson correlation was used for all features (data not shown). Soft power thresholds were selected

according to program recommendations as follows: biogenic amines – 3, polyphenols – 10, and lipids –

11.

We analyzed different groups of selected features for metabolic pathway enrichments. We formed

feature sets that combined data across all three LC-MS/MS datasets based on individual feature selection

analyses (t-test, PCA, and Boruta) or their presence only in manipulation samples. Dataset-specific

network modules were only analyzed with background features from the LC-MS/MS dataset they

belonged to and if the module was correlated to treatment (Student correlation $\geq |0.5|$, $p \leq 0.05$) (Fig. 2C).

We preformed Mummichog analyses on these feature sets (Li *et al.* 2013), as described in Results

& Discussion. This process matched 1,523 unique metabolite features to 6,725 KEGG annotated

compounds. For enrichment analyses combining features across datasets, we additionally used a

technique based on GSEA ranking features by t-scores returned by t-tests (Subramanian *et al.* 2005). In

network module pathway enrichment analyses, only Mummichog was used as it sets a hard threshold to

define a group of interest versus the background. Membership within or out of a network module was

simply defined and could be used for this division. All enrichment analyses were conducted through the

MetaboAnalyst interface with the following settings: Mixed ion mode, 3 ppm mass tolerance, retention

time included, primary ions not enforced, all adducts tested, default currency metabolites, and conducted

once for both the *Drosophila melanogaster* and *Saccharomyces cerevisiae* KEGG metabolic pathway and

compound databases (Fig. 2C). As we sought to characterize the composite metabolome of manipulated

ant heads containing both insect and fungal tissue, we chose both a well-studied insect and fungal model

organism to improve our odds of matching annotations. We did not use results from one database or the

other to discriminate between a host (ant) or parasite (fungus) signal. Neither of the databases would

represent the full metabolic repertoire of their respective model organisms and combining them could

offer more complete data for comparison. Furthermore, we wished to consider the possibility that due to

the relationship of the host and parasite, either organism may be producing metabolites canonically

associated with the other as part of its strategy in this antagonism.

746   We selected significantly enriched pathways based on one of the hypergeometric enrichment

results reported by MetaboAnalyst. When using Mummichog only (WGCNA module feature set), we

used the gamma-null adjusted p-value (≤ 0.05). When including a GSEA as a joint analysis (study-wide

feature set), we used the combined p-value (≤ 0.05), calculated with MetaboAnalyst using the Fisher

method. Of the overrepresented pathways selected by the enrichment analyses ($p \leq 0.05$), we further

imposed thresholds for: (*i*) a minimum of three selected features in the pathway, (*ii*) 1.25-fold enrichment,

and (*iii*) three DEGs (see below) encoding associated enzymes to discard weak signals that would likely

be difficult to interpret biologically in a multiomic pathway-level context (Fig. 2C). For cases when a

pathway was selected using both *D. melanogaster* and *S. cerevisiae* KEGG databases, a mean p-value and

fold-enrichment is reported.

756   **Multiomics integration of genomic and transcriptomic data:** We interpreted results of this

work's LC-MS/MS data in light of previously collected transcriptomic RNAseq data when possible (Will

et al. 2020). That RNAseq data was collected with a similar experimental framework, including

comparisons of gene expression of both *C. floridanus* and *O. camponoti-floridani* between a control

(uninfected ant or fungal culture) and manipulated ant samples. Identification of DEGs (Cuffdiff analysis

corrected FDR p ≤ 0.05, minimum two-fold change, minimum 4 RPKM) and relevant statistics are

reported in Will *et al.* 2020. For each enriched metabolic pathway, we retrieved gene sequence data for

enzymes associated with that pathway in KEGG (by enzyme nomenclature EC number). For each enzyme

EC, we extracted the first representative gene listed for *D. melanogaster* and *S. cerevisiae*. We searched

for reciprocal best matches to those genes in both the *C. floridanus* and *O. camponoti-floridani* genomes

using Proteinortho (v 5) with default settings (Lechner *et al.* 2011). While this non-exhaustive approach

would not identify every possible *C. floridanus* or *O. camponoti-floridani* gene with homology to known

enzymes of interest, it did assist with initially selecting pathway enrichments for deeper analysis. Per

pathway, we required that at least three DEGs combined from both transcriptomes of the ant and fungus

had homologs to the enzymes associated with that pathway. This selection criterion followed the

pathway-level thinking to require at least three contributing metabolite features matched by Mummichog

to consider an enrichment result for discussion. Metabolic pathway relationships were based on KEGG

data and supplemented by other sources where cited.

Data Availability

Genomic and transcriptomic data referenced here are available in Will *et al.* 2020 and the

GenBank accessions reported therein. Supplemental Data files (Supp. Data 1-4) are available upon

request while at the preprint stage.

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References

Acharjee, A., J. Larkman, Y. Xu, V. R. Cardoso, and G. V. Gkoutos, 2020 A random forest based

biomarker discovery and power analysis framework for diagnostics research. BMC Med. Genomics

13: 1–14.

Adamo, S. A., 2008 Norepinephrine and octopamine: linking stress and immune function across phyla.

ISJ 5: 12–19.

Adamo, S. A., 2019 Turning your victim into a collaborator: exploitation of insect behavioral control

systems by parasitic manipulators. Curr. Opin. Insect Sci. 33: 25–29.

Adamo, S. A., C. E. Linn, and N. E. Beckage, 2013 Parasites: evolution's neurobiologists. J. Exp. Biol.

216: 3–10.

Alecu, I., and S. A. L. Bennett, 2019 Dysregulated lipid metabolism and its role in α-synucleinopathy in

Parkinson's disease. Front. Neurosci. 13: 328.

Andersen, S. B., S. Gerritsma, K. M. Yusah, D. Mayntz, N. L. Hywel-Jones *et al.*, 2009 The Life of a

Dead Ant: The Expression of an Adaptive Extended Phenotype. Am. Nat. 174: 424–433.

Aonuma, H., 2020 Serotonergic control in initiating defensive responses to unexpected tactile stimuli in

the trap-jaw ant Odontomachus kuroiwae. J. Exp. Biol. 223:.

Aonuma, H., and T. Watanabe, 2012 Changes in the content of brain biogenic amine associated with early

colony establishment in the Queen of the ant, Formica japonica. PLoS One 7: e43377–e43377.

Bartzis, G., J. Deelen, J. Maia, W. Ligterink, H. W. M. Hilhorst *et al.*, 2017 Estimation of metabolite

networks with regard to a specific covariable: applications to plant and human data. Metabolomics

13: 129.

Batrakov, S. G., I. V. Konova, V. I. Sheichenko, S. E. Esipov, and L. A. Galanina, 2001 Two unusual

glycerophospholipids from a filamentous fungus, Absidia corymbifera. Biochim. Biophys. Acta -

Mol. Cell Biol. Lipids 1531: 169–177.

de Bekker, C., 2019 Ophiocordyceps–ant interactions as an integrative model to understand the molecular

basis of parasitic behavioral manipulation. Curr. Opin. Insect Sci. 33: 19–24.

de Bekker, C., W. C. Beckerson, and C. Elya, 2021 Mechanisms behind the Madness: How Do Zombie-

Making Fungal Entomopathogens Affect Host Behavior To Increase Transmission? (D. A. Garsin,

Ed.). MBio.

de Bekker, C., and B. Das, 2022 Hijacking time: How Ophiocordyceps fungi could be using ant host

clocks to manipulate behavior. Parasite Immunol. 44: e12909.

de Bekker, C., M. Merrow, and D. P. Hughes, 2014a From behavior to mechanisms: An integrative

approach to the manipulation by a parasitic fungus (Ophiocordyceps unilateralis s.l.) of its host ants

(Camponotus spp.). Integr. Comp. Biol. 52: 166–176.

de Bekker, C., R. A. Ohm, R. G. Loreto, A. Sebastian, I. Albert *et al.*, 2015 Gene expression during

zombie ant biting behavior reflects the complexity underlying fungal parasitic behavioral

manipulation. BMC Genomics 16: 620.

de Bekker, C., L. E. Quevillon, P. B. Smith, K. R. Fleming, D. Ghosh *et al.*, 2014b Species-specific Ant

Brain Manipulation by a Specialized Fungal Parasite. BMC Evol. Biol. 14: 166.

Boulay, R., V. Soroker, E. J. Godzinska, A. Hefetz, and A. Lenoir, 2000 Octopamine reverses the

isolation-induced increase introphallaxis in the carpenter ant Camponotus Fellah. Journgal Exp.

Biol. 203: 513–520.

Carlson, M. R. J., B. Zhang, Z. Fang, P. S. Mischel, S. Horvath *et al.*, 2006 Gene connectivity, function,

and sequence conservation: Predictions from modular yeast co-expression networks. BMC

Genomics 7: 1–15.

Cassilly, C. D., and T. B. Reynolds, 2018 PS, It's Complicated: The Roles of Phosphatidylserine and

Phosphatidylethanolamine in the Pathogenesis of Candida albicans and Other Microbial Pathogens.

J. Fungi 4:.

Coleman, C. M., and W. S. Neckameyer, 2005 Serotonin synthesis by two distinct enzymes in Drosophila

melanogaster. Arch. Insect Biochem. Physiol. 59: 12–31.

Colovic, M. B., D. Z. Krstic, T. D. Lazarevic-Pasti, A. M. Bondzic, and V. M. Vasic, 2013

Acetylcholinesterase Inhibitors: Pharmacology and Toxicology. Curr. Neuropharmacol. 11: 315.

Dakshinamurti, K., S. Dakshinamurti, M. P. Czubryt, K. Dakshinamurti, S. Dakshinamurti *et al.*, 2017

Vitamin B6: Effects of Deficiency, and Metabolic and Therapeutic Functions. Handb. Famine,

Starvation, Nutr. Deprivation 1–23.

Dawaliby, R., C. Trubbia, C. Delporte, C. Noyon, J. M. Ruysschaert *et al.*, 2016

Phosphatidylethanolamine Is a Key Regulator of Membrane Fluidity in Eukaryotic Cells. J. Biol.

Chem. 291: 3658.

Diez, L., P. Lejeune, and C. Detrain, 2014 Keep the nest clean: survival advantages of corpse removal in

ants. Biol. Lett. 10:.

Feng, P., Y. Shang, K. Cen, and C. Wang, 2015 Fungal biosynthesis of the bibenzoquinone oosporein to

evade insect immunity. Proc. Natl. Acad. Sci. U. S. A. 112: 11365–11370.

Fiehn Lab, 2020 ESI-MS-adducts-2020.

Fournier, D., J.-M. Bride, F. Hoffmann, and F. Karch, 1992 Acetylcholinesterase TWO TYPES OF

MODIFICATIONS CONFER RESISTANCE TO INSECTICIDE. J. Biol. Chem. 267: 14270–

14274.

Fredericksen, M. A., Y. Zhang, M. L. Hazen, R. G. Loreto, C. A. Mangold *et al.*, 2017 Three-dimensional

visualization and a deep-learning model reveal complex fungal parasite networks in behaviorally

manipulated ants. Proc. Natl. Acad. Sci. 114: 201711673.

Friedman, D. A., A. Pilko, D. Skowronska-Krawczyk, K. Krasinska, J. W. Parker *et al.*, 2018 The Role of

Dopamine in the Collective Regulation of Foraging in Harvester Ants. iScience 8: 283.

Gasparetti, C., E. Nordlund, J. Jänis, J. Buchert, and K. Kruus, 2012 Extracellular tyrosinase from the

fungus Trichoderma reesei shows product inhibition and different inhibition mechanism from the

intracellular tyrosinase from Agaricus bisporus. Biochim. Biophys. Acta - Proteins Proteomics

1824: 598–607.

Gauthier, M., 2010 *Insect Nicotinic Acetylcholine Receptors: State of the Art on Insect Nicotinic*

Acetylcholine Receptor Function in Learning and Memory (S. Hervé Thany, Ed.).

Geun, S. K., M. Nalini, Y. Kim, and D. W. Lee, 2009 Octopamine and 5-hydroxytryptamine mediate

866 hemocytic phagocytosis and nodule formation via eicosanoids in the beet armyworm, Spodoptera

867 exigua. Arch. Insect Biochem. Physiol. 70: 162–176.

868 Gillis, J., and P. Pavlidis, 2012 "Guilt by Association" Is the Exception Rather Than the Rule in Gene

869 Networks. PLOS Comput. Biol. 8: e1002444.

870 González-Santoyo, I., and A. Córdoba-Aguilar, 2012 Phenoloxidase: a key component of the insect

871 immune system. Entomol. Exp. Appl. 142: 1–16.

872 Gorman, M. J., and Y. Arakane, 2010 Tyrosine hydroxylase is required for cuticle sclerotization and

873 pigmentation in Tribolium castaneum. Insect Biochem. Mol. Biol. 40: 267–273.

874 Grünewald, B., and P. Siefert, 2019 Acetylcholine and Its Receptors in Honeybees: Involvement in

875 Development and Impairments by Neonicotinoids. Insects 10:.

876 Heil, M., 2016 Host Manipulation by Parasites: Cases, Patterns, and Remaining Doubts. Front. Ecol.

877 Evol. 4: 80.

878 Helluy, S., 2013 Parasite-induced alterations of sensorimotor pathways in gammarids: collateral damage

879 of neuroinflammation? J. Exp. Biol. 216: 67–77.

880 Helluy, S., and J. C. Holmes, 1990 Serotonin, octopamine, and the clinging behavior induced by the

881 parasite Polymorphus paradoxus (Acanthocephala) in Gammarus lacustris (Crustacea). Can. J. Zool.

882 68: 1214–1220.

883 Herbison, R. E. H., 2017 Lessons in Mind Control: Trends in Research on the Molecular Mechanisms

884 behind Parasite-Host Behavioral Manipulation. Front. Ecol. Evol. 5: 102.

885 Hoxmeier, J. C., B. D. Thompson, C. D. Broeckling, P. Small, B. D. Foy *et al.*, 2015 Analysis of the

886 metabolome of Anopheles gambiae mosquito after exposure to Mycobacterium ulcerans. Sci.

887 Reports 2015 51 5: 1–8.

888 Hughes, D. P., S. B. Andersen, N. L. Hywel-Jones, W. Himaman, J. Billen *et al.*, 2011 Behavioral

889 mechanisms and morphological symptoms of zombie ants dying from fungal infection. BMC Ecol.

890 11: 13.

891 Johansen, J., M. E. Halpern, K. M. Johansen, and H. Keshishian, 1989 Stereotypic morphology of

glutamatergic synapses on identified muscle cells of Drosophila larvae. J. Neurosci. 9: 710.

Kachman, M., H. Habra, W. Duren, J. Wigginton, P. Sajjakulnukit *et al.*, 2020 Deep annotation of

untargeted LC-MS metabolomics data with Binner. Bioinformatics 36: 1801–1806.

Kamhi, J. F., S. Arganda, C. S. Moreau, and J. F. A. Traniello, 2017 Origins of aminergic regulation of

behavior in complex insect social systems. Front. Syst. Neurosci. 11: 74.

Kanehisa, M., and S. Goto, 2000 KEGG: Kyoto Encyclopedia of Genes and Genomes. Nucleic Acids

Res. 28: 27.

Kassambara, A., M. Kosinski, P. Biecek, and S. Fabian, 2019 Drawing Survival Curves using "ggplot2"

[R package survminer version 0.4.4].

Kim, Y. H., and S. H. Lee, 2013 Which acetylcholinesterase functions as the main catalytic enzyme in the

Class Insecta? Insect Biochem. Mol. Biol. 43: 47–53.

Kind, T., K. H. Liu, D. Y. Lee, B. Defelice, J. K. Meissen *et al.*, 2013 LipidBlast in silico tandem mass

spectrometry database for lipid identification. Nat. Methods 2013 108 10: 755–758.

Kobmoo, N., D. Wichadakul, N. Arnamnart, R. C. Rodríguez De La Vega, J.-J. J. Luangsa-ard *et al.*,

2018 A genome scan of diversifying selection in Ophiocordyceps zombie-ant fungi suggests a role

for enterotoxins in co-evolution and host specificity. Mol. Ecol. 27: 3582–3598.

Kursa, M. B., and W. R. Rudnicki, 2010 Feature Selection with the Boruta Package. J. Stat. Softw. 36: 1–

13.

Lafferty, K. D., and J. C. Shaw, 2013 Comparing mechanisms of host manipulation across host and

parasite taxa. J. Exp. Biol. 216: 56–66.

Langfelder, P., and S. Horvath, 2008 WGCNA: an R package for weighted correlation network analysis.

BMC Bioinformatics 9: 559.

Leboeuf, A. C., P. Waridel, C. S. Brent, A. N. Gonçalves, L. Menin *et al.*, 2016 Oral transfer of chemical

cues, growth proteins and hormones in social insects. Elife 5:.

Lechner, M., S. Findeiß, L. Steiner, M. Marz, P. F. Stadler *et al.*, 2011 Proteinortho: Detection of (Co-

)orthologs in large-scale analysis. BMC Bioinformatics 12: 1–9.

Lee, Y. S., Y. S. Park, S. Nam, S. J. Suh, J. Lee *et al.*, 2000 Characterization of GAR-2, a Novel G

Protein-Linked Acetylcholine Receptor from Caenorhabditis elegans. J. Neurochem. 75: 1800–1809.

Lefèvre, T., S. A. Adamo, D. G. Biron, D. Missé, D. Hughes *et al.*, 2009 Invasion of the body snatchers:

the diversity and evolution of manipulative strategies in host-parasite interactions. Adv. Parasitol.

68: 45–83.

Li, S., Y. Park, S. Duraisingham, F. H. Strobel, N. Khan *et al.*, 2013 Predicting Network Activity from

High Throughput Metabolomics. PLOS Comput. Biol. 9: e1003123.

Li, Z., and D. E. Vance, 2008 Thematic Review Series: Glycerolipids. Phosphatidylcholine and choline

homeostasis. J. Lipid Res. 49: 1187–1194.

Libersat, F., M. Kaiser, and S. Emanuel, 2018 Mind Control: How Parasites Manipulate Cognitive

Functions in Their Insect Hosts. Front. Psychol. 9: 572.

Loreto, R. G., and D. P. Hughes, 2019 The metabolic alteration and apparent preservation of the zombie

ant brain. J. Insect Physiol. 118: 103918.

Lovett, B., R. J. St. Leger, and H. H. de Fine Licht, 2020 Going gentle into that pathogen-induced

goodnight. J. Invertebr. Pathol. 174: 107398.

Mangold, C. A., M. J. Ishler, R. G. Loreto, M. L. Hazen, and D. P. Hughes, 2019 Zombie ant death grip

due to hypercontracted mandibular muscles. J. Exp. Biol. 222: jeb200683.

Matyash, V., G. Liebisch, T. V. Kurzchalia, A. Shevchenko, and D. Schwudke, 2008 Lipid extraction by

methyl-tert-butyl ether for high-throughput lipidomics. J. Lipid Res. 49: 1137–1146.

Moore, J., 2013 An overview of parasite-induced behavioral alterations - and some lessons from bats. J.

Exp. Biol. 216: 11–7.

Muscedere, M. L., N. Johnson, B. C. Gillis, J. F. Kamhi, and J. F. A. Traniello, 2012 Serotonin modulates

worker responsiveness to trail pheromone in the ant Pheidole dentata. J. Comp. Physiol. A

Neuroethol. Sensory, Neural, Behav. Physiol. 198: 219–227.

Neckameyer, W. S., C. M. Coleman, S. Eadie, and S. F. Goodwin, 2007 Compartmentalization of

neuronal and peripheral serotonin synthesis in Drosophila melanogaster. Genes, Brain Behav. 6:

756–769.

Neckameyer, W. S., and K. White, 1992 A single locus encodes both phenylalanine hydroxylase and tryptophan hydroxylase activities in Drosophila. J. Biol. Chem. 267: 4199–4206.

Nosanchuk, J. D., and A. Casadevall, 2006 Impact of melanin on microbial virulence and clinical resistance to antimicrobial compounds. Antimicrob. Agents Chemother. 50: 3519–3528.

Nosanchuk, J. D., R. E. Stark, and A. Casadevall, 2015 Fungal melanin: What do we know about structure? Front. Microbiol. 6: 1463.

Pang, Z., J. Chong, G. Zhou, D. A. De Lima Morais, L. Chang *et al.*, 2021 MetaboAnalyst 5.0: narrowing the gap between raw spectra and functional insights. Nucleic Acids Res. 49: W388–W396.

Pflüger, H. J., and C. Duch, 2011 Dynamic neural control of insect muscle metabolism related to motor behavior. Physiology 26: 293–303.

Piao, S., Y. L. Song, H. K. Jung, Y. P. Sam, W. P. Ji *et al.*, 2005 Crystal structure of a clip-domain serine protease and functional roles of the clip domains. EMBO J. 24: 4404.

Pokotylo, I., P. Pejchar, M. Potocký, D. Kocourková, Z. Krčková *et al.*, 2013 The plant non-specific phospholipase C gene family. Novel competitors in lipid signalling. Prog. Lipid Res. 52: 62–79.

Pontoppidan, M. B., W. Himaman, N. L. Hywel-Jones, J. J. Boomsma, and D. P. Hughes, 2009 Graveyards on the move: The spatio-temporal distribution of dead ophiocordyceps-infected ants (A. Dornhaus, Ed.). PLoS One 4: e4835.

Prandovszky, E., E. Gaskell, H. Martin, J. P. Dubey, J. P. Webster *et al.*, 2011 The Neurotropic Parasite Toxoplasma Gondii Increases Dopamine Metabolism. PLoS One 6: e23866.

Quinn, D. M., 1987 Acetylcholinesterase: Enzyme Structure, Reaction Dynamics, and Virtual Transition States. Chem. Reiviews 87: 955–979.

R Core Team, 2021 R: A language and environment for statistical computing.

Ramirez, J. L., E. J. Muturi, C. Dunlap, and A. P. Rooney, 2018 Strain-specific pathogenicity and subversion of phenoloxidase activity in the mosquito Aedes aegypti by members of the fungal entomopathogenic genus Isaria. Sci. Reports 2018 81 8: 1–12.

RStudio Team, 2015 RStudio: Integrated Development for R.

Sakolrak, B., R. Blatrix, U. Sangwanit, and N. Kobmoo, 2018 Experimental infection of the ant

Polyrhachis furcata with Ophiocordyceps reveals specificity of behavioural manipulation. Fungal

Ecol. 33: 122–124.

Selinheimo, E., M. Saloheimo, E. Ahola, A. Westerholm-Parvinen, N. Kalkkinen *et al.*, 2006 Production

and characterization of a secreted, C-terminally processed tyrosinase from the filamentous fungus

Trichoderma reesei. FEBS J. 273: 4322–4335.

Shaw, J. C., W. J. Korzan, R. E. Carpenter, A. M. Kuris, K. D. Lafferty *et al.*, 2009 Parasite manipulation

of brain monoamines in California killifish (Fundulus parvipinnis) by the trematode Euhaplorchis

californiensis. Proc. R. Soc. B Biol. Sci. 276: 1137–1146.

Shyu, P., B. S. H. Ng, N. Ho, R. Chaw, Y. L. Seah *et al.*, 2019 Membrane phospholipid alteration causes

chronic ER stress through early degradation of homeostatic ER-resident proteins. Sci. Reports 2019

91 9: 1–15.

Singh, K. D., R. K. Labala, T. B. Devi, N. I. Singh, H. D. Chanu *et al.*, 2017 Biochemical efficacy,

molecular docking and inhibitory effect of 2, 3-dimethylmaleic anhydride on insect

acetylcholinesterase. Sci. Reports 2017 71 7: 1–11.

Stuart, J. M., E. Segal, D. Koller, and S. K. Kim, 2003 A gene-coexpression network for global discovery

of conserved genetic modules. Science (80-.). 302: 249–255.

Subramanian, A., P. Tamayo, V. K. Mootha, S. Mukherjee, B. L. Ebert *et al.*, 2005 Gene set enrichment

analysis: A knowledge-based approach for interpreting genome-wide expression profiles. Proc. Natl.

Acad. Sci. U. S. A. 102: 15545–15550.

Sugumaran, M., and H. Barek, 2016 Critical Analysis of the Melanogenic Pathway in Insects and Higher

Animals. Int. J. Mol. Sci. 17:.

Szczuka, A., J. Korczyńska, A. Wnuk, B. Symonowicz, A. Gonzalez Szwacka *et al.*, 2013 The effects of

serotonin, dopamine, octopamine and tyramine on behavior of workers of the ant Formica polyctena

during dyadic aggression tests. Acta Neurobiol. Exp. (Wars). 73: 495–520.

Therneau, T., 2015 A Package for Survival Analysis in S.

Thomas, F., R. Poulin, and J. Brodeur, 2010 Host manipulation by parasites: A multidimensional

phenomenon. Oikos 119: 1217–1223.

Trinh, T., R. Ouellette, and C. de Bekker, 2021 Getting lost: the fungal hijacking of ant foraging

behaviour in space and time. Anim. Behav. 181: 165–184.

Tsugawa, H., T. Cajka, T. Kind, Y. Ma, B. Higgins *et al.*, 2015 MS-DIAL: data-independent MS/MS

deconvolution for comprehensive metabolome analysis. Nat. Methods 2015 126 12: 523–526.

VanderMolen, K. M., H. A. Raja, T. El-Elimat, and N. H. Oberlies, 2013 Evaluation of culture media for

the production of secondary metabolites in a natural products screening program. AMB Express 3:

71.

van der Veen, J. N., J. P. Kennelly, S. Wan, J. E. Vance, D. E. Vance *et al.*, 2017 The critical role of

phosphatidylcholine and phosphatidylethanolamine metabolism in health and disease. Biochim.

Biophys. Acta - Biomembr. 1859: 1558–1572.

Verlinden, H., 2018 Dopamine signalling in locusts and other insects. Insect Biochem. Mol. Biol. 97: 40–

52.

Walter, A., U. Korth, M. Hilgert, J. Hartmann, O. Weichel *et al.*, 2004 Glycerophosphocholine is elevated

in cerebrospinal fluid of Alzheimer patients. Neurobiol. Aging 25: 1299–1303.

Wang, Y., H. Jiang, Y. Cheng, C. An, Y. Chu *et al.*, 2017 Activation of Aedes aegypti prophenoloxidase-

3 and its role in the immune response against entomopathogenic fungus. Insect Mol. Biol. 26: 552.

Will, I., W. C. Beckerson, and C. de Bekker, 2022 Using machine learning to predict protein-protein

interactions between a zombie ant fungus and its carpenter ant host. bioRxiv 2022.09.09.507359.

Will, I., B. Das, T. Trinh, A. Brachmann, R. A. Ohm *et al.*, 2020 Genetic Underpinnings of Host

Manipulation by Ophiocordyceps as Revealed by Comparative Transcriptomics. G3 (Bethesda). 10:

2275–2296.

Yakovlev, I. K., 2018 Effects of Octopamine on Aggressive Behavior in Red Wood Ants. Neurosci.

Behav. Physiol. 2018 483 48: 279–288.

Zheng, S., R. Loreto, P. Smith, A. Patterson, D. Hughes *et al.*, 2019 Specialist and Generalist Fungal

Parasites Induce Distinct Biochemical Changes in the Mandible Muscles of Their Host. Int. J. Mol.

Sci. 20:.

Zhuang, J. X., Y. H. Hu, M. H. Yang, F. J. Liu, L. Qiu *et al.*, 2010 Irreversible Competitive Inhibitory

Kinetics of Cardol Triene on Mushroom Tyrosinase. J. Agric. Food Chem. 58: 12993–12998.

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