Host transcriptional responses and SARS-CoV-2 isolates from the nasopharyngeal samples of Bangladeshi COVID-19 patients

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Abstract

As the COVID-19 pandemic progresses, fatality and cases of new infections are also increasing at an alarming rate. SARS-CoV-2 follows a highly variable course and it is becoming more evident that individual's immune system has a decisive influence on the progression of the disease. However, the detailed underlying molecular mechanisms of the SARS-CoV-2 mediate disease pathogenesis are largely unknown. Only a few host transcriptional responses in COVID-19 have been reported so far from the Western world, but no such data has been generated from the South-Asian region yet to correlate the conjectured lower fatality around this part of the globe. In this context, we aimed to perform the transcriptomic profiling of the COVID-19 patients from Bangladesh along with the reporting of the SARS-CoV-2 isolates from these patients. Moreover, we performed a comparative analysis to demonstrate how differently the various SARS-CoV-2 infection systems are responding to the viral pathogen. We detected a unique missense mutation at 10329 position of ORF1ab gene, annotated to 3C like proteinase, which is found in 75% of our analyzed isolates; but is very rare globally. Upon the functional enrichment analyses of differentially modulated genes, we detected a similar host induced response reported earlier; this response was mainly mediated by the innate immune system, interferon stimulation, and upregulated cytokine expression etc. in the Bangladeshi patients. Surprisingly, we did not perceive the induction of apoptotic signaling, phagosome formation, antigen presentation and production, hypoxia response within these nasopharyngeal samples. Furthermore, while comparing with the other SARS-CoV-2 infection systems, we spotted that lung cells trigger the more versatile immune and cytokine signaling which was several folds higher compared to our reported nasopharyngeal samples. We also observed that lung cells did not express *ACE2* in a very high amount as suspected, however, the nasopharyngeal cells are found overexpressing *ACE2*. But the amount of *DPP4* expression within the nasal samples was significantly lower compared to the other cell types. Surprisingly, we observed that lung cells express a very high amount of integrins compared to the nasopharyngeal samples, which might suggest the putative reasons for an increased amount of viral infections in the lungs. From the network analysis, we got clues on the probable viral modulation for the overexpression of these integrins. Our data will provide valuable insights in developing potential studies to elucidate the roles of ethnicity effect on the viral pathogenesis, and incorporation of further data will enrich the search of an effective therapeutics.

Introduction

Since the declaration of COVID-19 pandemic on 11 March, this Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) mediated infection has spread ~213 countries and territories [1]. Approximately, 15 million individuals across the globe have fallen victim to this virus and the number is constantly increasing at an alarming rate, as of the writing of this manuscript [1]. Though the initial fatality percentage was as low as 3.5%, currently this value lies around ~6.66% [1] and it might be increased because of the withdrawal of earlier preventing measures taken throughout the world. Coronaviruses are not new to human civilization, as these viruses caused several earlier outbreaks during the past two decades. However, none of the earlier outbreaks spread as widely as the current ongoing pandemic. As the pandemic progresses, more researches on the molecular pathobiology of the COVID-19 are being rapidly carried out to search for effective therapeutic intervention.

Coronaviruses possess single-stranded RNA (positive sense) genomes lengthening approximately 30Kb [2]. Amongst the coronaviruses, SARS-CoV-2 is a member of the betacoronaviruses having a ~29.9Kb genome which contains 11 functional genes [3]. Though SARS-CoV-2 shows similar clinical characteristics as Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV) and Middle East Respiratory Syndrome-related Coronavirus (MERS-CoV) viruses, it has only ~79% and ~50% genome sequence similarities with these viruses, respectively; whereas, the genome sequence of SARS-CoV-2 is ~90% identical to that of bat derived SARS-like coronavirus [4]. Moreover, several key genomic variances between SARS-CoV-2 and SARS-CoV such as- 380 different amino acid substitutions, ORF8a deletion, ORF8b elongation, and ORF3b truncation were also reported [2].

The clinical characteristics of the COVID-19 range from mild fever to severe lung injury [5]. Some of the commonly observed mild COVID-19 symptoms are- fever, cough, and fatigue; however, complications such as- myalgia, shortness of breath, headache, diarrhea, and sore throat were also reported [6]. Furthermore, severely affected patients had exhibited respiratory complications like- moderate to severe pneumonia, acute respiratory distress syndrome (ARDS), sepsis, acute lung injury (ALI), and multiple organ dysfunction (MOD) [7]. Primarily, the lungs of the COVID-19 patients are affected [8]; however, failures of other functional systems, namely- cardiovascular system, nervous system etc. were also reported [9, 10].

Several features of the SARS-CoV-2 infection made it more complicated for effective clinical

management. From the earlier studies, the incubation period of SARS-CoV-2 was reported to

be around 4-5 days, however, some recent studies suggested a prolonged incubation period of

8-27 days [11]. Additionally, several cases of viral latency within the host [12], and the

recurrent presence of SARS-CoV-2 in clinically recovered patients were also recorded [13,

14]. However, the detailed molecular mechanism behind these phenomena is still elusive.

In COVID-19, an increased level infection associated pro-inflammatory cytokines were

recorded [15], which thereby supports the term "Cytokine storm", that was frequently used to

describe the SARS-CoV and MERS-CoV disease pathobiology [16]. This phenomenon

causes the hyperactivation and recruitment of the inflammatory cells within the lungs and

results in the acute lung injury of the infected patients [17]. However, this illustrates one

putative molecular mechanism of COVID-19, there are many other immune regulators and

host genetic/epigenetic factors which can also play significant contribution towards the

disease manifestation [18, 19]. This multifaceted regulation was also reported previously for

other different coronavirus infections [20]. Host-pathogen interactions in different

coronavirus infections can function as a double-edged sword, as these could be beneficial not

only to the hosts but also the viruses [20]. Similar host-virus tug-of-war can also occur in

COVID-19 which might be contributing towards the overcomplicated disease outcomes [21].

Collectively, more than 1.7 million (almost 9% of the total infections around the globe)

people have been diagnosed with COVID-19 in the South-Asian region and the number is

still increasing devastatingly [1]. Recently, it has been speculated that South-Asian people

might be possessing a genomic region acting as the risk factor for COVID-19 [22]. Moreover,

another study suggested some genomic variations in several Indian SARS-CoV-2 isolates that

might be involved in the COVID-19 pathogenesis in Indian patients [23]. However, any data

suggesting the COVID-19 patients' transcriptomic responses from this part of the globe are

yet to be reported.

Several previously conducted studies reported the host transcriptional responses in SARS-

CoV-2 infections using patient samples, animal models, and cell lines to explain the

pathobiology of COVID-19 [24-26]. However, a detailed comparison of the host

transcriptional responses between these different infection models as well as the different

sites of the respiratory system is still lacking; but it might provide valuable insights on the

COVID-19 pathogenesis and disease severity. In this present study, we sought to discuss the

host transcriptional responses observed in COVID-19 patients in Bangladesh. Additionally, we reported the genome variations observed in the four SARS-CoV-2 isolates obtained from these patients. Finally, we illuminated the differences in host transcriptional responses in different COVID-19 infection models and further pursued to discover the putative effects of these altered responses.

Materials and Methods

Sample collection and virus detection by Real-time reverse transcription-quantitative PCR (RT-qPCR)

The nasopharyngeal swab samples were collected from patients suspicious of COVID-19 and placed in sample collection vial containing normal saline. Collected samples were preserved at -20°C until further use for RNA extraction and RT-qPCR assay. The RT-qPCR was performed for ORF1ab and N genes of SARS-CoV-2 using Novel Coronavirus (2019-nCoV) Nucleic Acid Diagnostic Kit (PCR-Fluorescence Probing) of Sansure Biotech Inc. according to the manufacturer's instructions. RNA was extracted from a 20 μL swab sample through lysis with sample release reagent provided by the kit and then directly used for RT-qPCR. Thermal cycling was performed at 50 °C for 30 min for reverse transcription, followed by 95 °C for 1 min and then 45 cycles of 95 °C for 15 s, 60 °C for 30 s on an Analytik-Jena qTOWER instrument (Analytik Jena, Germany).

RNA sequencing

Total RNA was extracted from nasopharyngeal swab samples (labeled as S2, S3, S4, S9) collected from SARS-COV-2 infected COVID-19 patients using TRIzol (Invitrogen) reagent following the manufacturer's protocol. RNA-seq libraries were prepared from total RNA using TruSeq Stranded Total RNA Library Prep kit (Illumina) according to the manufacturer's instructions where the first-strand cDNA was synthesized using SuperScript II Reverse Transcriptase (Thermo Fisher) and random primers. Paired-end (150 bp reads) sequencing of the RNA library was performed on the Illumina NextSeq 500 platform.

Data processing and identification of the viral agent

Firstly, the sequencing reads were adapter and quality trimmed using the Trimmomatic program [27]. The remaining reads were mapped against the SARS-CoV-2 reference

151 sequence (NC_045512.2) using Bowtie 2 [28]. Then the mapped reads were assembled de

152 novo using Megahit (v.1.1.3) [29].

Mapping of the RNA-seq reads onto SARS-CoV-2 reference genome

154 We mapped the normalized (by count per million mapped reads-CPM) RNA-seq reads onto

155 the SARS-CoV-2 genome track of the UCSC genome browser [30] using the "bamCoverage"

156 feature of deepTools2 suite [31].

Identification of SARS-CoV-2 genome variations and variation annotation

We identified the variations within our sequenced SARS-CoV-2 genome using the "Variation

Identification" (https://bigd.big.ac.cn/ncov/online/tool/variation) tool of "2019 Novel

Coronavirus Resource (2019nCoVR)" portal of China National Center for Bioinformation

[32]. We then annotated the variations of the isolated SARS-CoV-2 isolates using the

"Variation Annotation" (https://bigd.big.ac.cn/ncov/online/tool/annotation) tool from the

same portal [32]. We also gathered the global frequency of every identified variation using

this same information portal [32]. Different representations showing the information

regarding the variations were produced using the Microsoft Excel program [33]. The impacts

of the variations were further characterized utilizing the Ensembl Variant Effect Predictor

(VEP) tool [34].

Analysis of RNA-seq expression data

We analyzed both our RNA-seq and some publicly available RNA-seq data for COVID-19

host transcriptional profile analysis. Publicly available Illumina sequenced RNA-seq raw

FastQ reads were extracted from the GEO database (accessions of the data used can be found

in supplementary file 1) [35]. We have checked the raw sequence quality using FastQC

program (v0.11.9) [36] and found that the "Per base sequence quality", and "Per sequence

quality scores" were high over the threshold for all sequences (Supplementary file 2). The

mapping of reads was done with TopHat (tophat v2.1.1 with Bowtie v2.4.1) [37]. Short reads

were uniquely aligned allowing at best two mismatches to the human reference genome from

(GRCh38) as downloaded from the UCSC database [38]. Sequence matched exactly more

than one place with equally quality were discarded to avoid bias [39]. The reads that were not

mapped to the genome were utilized to map against the transcriptome (junctions mapping).

Ensembl gene model [40] (version 99, as extracted from UCSC) was used for this process.

After mapping, we used the SubRead package featureCount (v2.21) [41] to calculate absolute

read abundance (read count, rc) for each transcript/gene associated to the Ensembl genes. For
differential expression (DE) analysis we used DESeq2 (v1.26.0) with R (v3.6.2; 2019-07-05)
[42] that uses a model based on the negative binomial distribution. To avoid false positive,
we considered only those transcripts where at least 10 reads are annotated in at least one of
the samples used in this study and also applied a minimum Log2 fold change of 0.5 for to be
differentially apart from adjusted p-value cut-off of ≤ 0.05 by FDR. To assess the fidelity of
the RNA-seq data used in this study and normalization method applied here, we checked the
normalized Log2 expression data quality using R/Bioconductor package
"arrayQualityMetrics (v3.44.0)" [43]. From these analyses, no outlier was detected in our
data by "Distance between arrays", "Boxplots", and "MA plots" methods and replicate
samples are clustered together (data not shown). We also performed a multifactorial
differential gene expression analysis using the edgeR tool [44] following the experimental
design- (Sample A/control for sample A)/(Sample B/control for sample B).

Construction of phylogenetic tree

We constructed a Neighbour-Joining phylogenetic tree with all available 145 SARS-CoV-2
genomes of Bangladeshi isolates (retrieved on 6th May from GISAID [45]). Firstly, the
genome sequences were aligned using MAFFT [46] tool using the auto-configuration. Then
we used MEGA X [47] for constructing the phylogenetic tree utilizing 500 bootstrapping
with substitution model/method: maximum composite likelihood, uniform rates of variation
among sites, the partial deletion of gaps/missing data and site coverage cutoff 95%.

Functional enrichment analysis

203 We utilized Gitools (v1.8.4) for enrichment analysis and heatmap generation [48]. We have
204 utilized the Gene Ontology Biological Processes (GOBP) [49], Bioplanet pathways [50],
205 KEGG pathway [51], and Reactome pathway [52] modules for the overrepresentation
206 analysis. Resulting p-values were adjusted for multiple testing using the Benjamin and
207 Hochberg's method of False Discovery Rate (FDR) [53].

Retrieval of the host proteins that interact with SARS-CoV-2

209 We have obtained the list of human proteins that form high confidence interactions with
210 SARS-CoV-2 proteins from conducted previously study [21] and processed their provided
211 protein names into the associated HGNC official gene symbols.

Construction of biological networks

Construction, visualization, and analysis of biological networks with differentially expressed genes, their associated transcription factors, and interacting viral proteins were executed in the Cytoscape software (v3.8.0) [54]. We used the STRING [55] database to extract the highest confidences (0.9) edges only for the protein-protein interactions to reduce any false positive connection.

Results

Our sequenced SARS-CoV-2 isolates showed a divergent variation pattern compared to the other Bangladeshi isolates

We sought to find out the genome variations within the four SARS-CoV-2 isolates we sequenced and pursued the deviation of these genomes compared to the other isolates in Bangladesh. To accomplish these goals, we first identified and annotated the genome variations observed within our sequenced isolates. Then we produced informative statistics from these observed variations and compared the prevalence of those with the other isolates of Bangladesh and the rest of the world.

We mapped the RNA-seq reads of each of the samples and checked their distribution athwart the entire reference genome of SARS-CoV-2 (Figure 1A). High coverages and read evidence were observed for all the isolates across the whole genome of the SARS-CoV-2 (Figure 1A). This suggests that the sequenced genomes of these isolates are of high coverage and no such region is observed without the mapped reads.

We detected sixty different types of variations within these four analyzed SARS-CoV-2 isolates (Table 1). All the four different types of sequence variations were spotted in these isolates, however, single nucleotide polymorphisms (SNPs) were most prominent (Figure 1B). Among these variations, twelve variations were found in more than one isolate, whereas rest forty-eight variation occurred in only one isolate (Table 1, Figure 1C). Among the isolates, isolate S3 contained the lowest number of variations, whereas isolate S4 has the highest number of variations (Figure 1D). Most of these variations are intergenic variants that occurred either in the 5'-UTR or 3'-UTR regions (Figure 1C-D); whereas, globally most variations have occurred in the ORF1ab gene. Surprisingly, out of all these variations, we found only one downstream gene variation on the 3'-UTRs of all the four isolates; this

variation can potentially impact the regulation of the ORF10 gene (Figure 1D). Most of the
nucleic acid mutations were located on the 3'-UTR of the isolates, whereas the ORF1ab gene
contained most of the amino acid mutations (Figure 1E).

No highly severe mutation was identified amongst these variations, but we found nine
moderately impacting, seven low impacting, and forty-seven modifier variations within these
isolates (Figure 1F, Supplementary file 3). As of 8th July, thirty-eight out of the sixty
variations within our sequenced isolates were completely absent in all other Bangladeshi
SARS-CoV-2 isolates (Table 1). Strikingly, we observed that variation 10329: A>G is
present within three of our sequenced isolates, only one other Bangladeshi and one other
USA isolate contain this variation (Figure 1G). This variation is located within the 3C-like
protease of SARS-CoV-2. Previously, the potential implication of the mutations of this
protein was reported to alter its overall structure and functionality [56-58] in SARS-CoV.
Also, few of our reported variations like 25505: A>T and 29392: G>T are not highly
prevalent globally (Figure 1G).

Exploring the Nextstrain portal [59], we noticed that our analyzed SARS-CoV-2 sequences
are closely placed to the Saudi-Arabian isolates (Supplementary Figure 1); although, most of
the other Bangladeshi isolates were placed in the major European clusters (data not shown).
Furthermore, these isolates analyzed in this study is distinctly placed in our constructed
Neighbor-Joining phylogenetic tree (Figure 2), this also supports the differences between
these isolates and other Bangladeshi SARS-CoV-2 isolates which might have been originated
from the European nations.

Stimulated antiviral immune responses are detected in the nasopharyngeal
samples of Bangladeshi COVID-19 patients

Though initial researches suggested the potential implication of viral variations on the
COVID-19 disease severity, one recent study indicated otherwise; Several host factors such
as- abnormal immune responses, cytokine signaling etc. might be influencing the overall
disease outcomes more prominently compared to the viral mutations [60]. Moreover, several
data surmised that ethnicity might be a pivotal risk factor of being susceptible to COVID-19
[61].

In this context, we explored the transcriptome data obtained from the nasopharyngeal
samples from Bangladeshi COVID-19 patients to find out how these patients were

responding against the invading SARS-CoV-2. We compared the RNA-seq data of these

patients with some random normal individuals' nasopharyngeal RNA-seq data to find out the

differentially expressed genes within our analyzed samples. We observed a roughly constant

standard deviation for the normalized reads suggesting a lesser amount of variation occurred

during the normalization (Figure 3A). Furthermore, we performed sample clustering to assess

the quality of our generated normalized RNA-seq data. No anomalies were observed in the

sample to sample distance matrix (Figure 3B) and principal component analysis (PCA)

(Figure 3C) while comparing our samples with the used healthy individuals' data. Moreover,

the larger differences observed in the PCA plot (Figure 3C) and clustered heatmap of the

count matrix with the top 50 significant genes (Figure 3D) suggest a significant

transcriptomic response difference between our infected patients' data and the normal

individuals' data. Likewise, the sample to sample distance plot suggested the similarities of

samples of similar nature; the infected and healthy samples were clustered into two distinct

groups (Figure 3B).

Sungnak et al. described the significance of several viral entry associated host proteins in

SARS-CoV-2 pathogenesis, namely- ACE2, TMPRSS2, BSG, CTSL, DPP4 [62]. We also

investigated the expression of the associated transcripts of these proteins within our patients'

samples. We spotted that both the healthy and infected samples have expressed these genes

except the *DPP4* gene (Figure 3E).

We identified 1,614 differentially expressed genes within our reported four SARS-CoV-2

infected nasopharyngeal samples; among these differentially expressed genes, 558 genes

were upregulated, and 1056 genes were downregulated (Supplementary file 4). Then we

sought to discover in which biological functions/pathways these deregulated genes might be

involved. To achieve this, we performed functional enrichment analyses with the observed

deregulated genes using different ontology and pathway modules.

Several GOBP terms related to antiviral immune responses such as- viral process, defense

response to virus, innate immune response, inflammatory response, negative regulation of

viral transcription, negative regulation of viral genome replication etc. were observed

enriched for the upregulated genes (Figure 3F, Supplementary Figure 2). Surprisingly, several

other important antiviral defense related functions such as- apoptosis, antigen processing, and

presentation etc. were found enriched for downregulated genes (Figure 3F). Similarly, this

pattern was also observed for the functional enrichment using KEGG and Bioplanet pathways

modules. Upregulated genes are observed involved in signaling pathways such as- innate

immune system, antiviral mechanism by interferon-stimulated genes, interleukin-2 signaling,

interferon-gamma signaling, interferon alpha-beta signaling, antiviral mechanism by

interferon stimulated genes, IL-17 signaling pathway, Toll-like receptor signaling pathway,

RIG-I like receptor signaling pathway, and MAPK signaling pathway, etc. (Figure 3G-H,

Supplementary Figure 2). Strikingly, several important antiviral signaling pathways such as-

antigen processing and presentation, apoptosis, HIF-1 signaling pathway, Natural killer cell

mediated cytotoxicity, phagosome, PI3K-Akt signaling pathway, Interleukin-6 regulation of

target genes, and Interleukin-10 inflammatory signaling pathway were enriched for the

downregulated genes (Figure 3G-H). This unusual observation made us curious to search for

a similar pattern of deregulated host responses in several other COVID-19 disease models.

Host responses observed in nasopharyngeal samples are significantly different compared to the other SARS-CoV-2 infections models

We sought to compare the host responses of our analyzed samples with several other different

SARS-CoV-2 infection models (two different lung biopsy samples from COVID-19 patients

and two different cell lines). We performed functional enrichment analyses using

differentially expressed genes from four other SARS-CoV-2 infection systems and compared

the enriched terms of our samples with these four other samples. Moreover, how the host

responds differently in different tissue types were also evaluated. To achieve these goals, we

identified the differentially expressed genes across these different samples and systematically

compared the enrichment results of those deregulated genes.

Using the similar parameterization of the differential gene expression analyses, we identified

6714 genes in lung cells (GSE147507), 232 genes in lung cells (GSE150316), 143 genes in

NHBE cells (GSE147507), and 5637 genes in Calu-3 cells (GSE148729) as differentially

expressed compared to their respective healthy controls (Supplementary file 5). Significant

proportions of the deregulated genes detected in our nasopharyngeal samples are also found

deregulated in lung (GSE147507) and Calu-3 cells (GSE148729) samples (Figure 4A), while

a small number of our samples' deregulated genes were also observed deregulated in rest of

the two samples used (Figure 4A).

Enrichment analysis using these deregulated genes suggested the host response differences

among the different infection systems used (Figure 4B-D). Upon the analysis, only a few

GOBP terms were found enriched for both our samples, lung (GSE147507), and Calu-3 cells

(GSE148729) samples, such as- viral process, immune response, innate immune response,
defense response to virus, interferon signaling etc. (Figure 4B). However, genes in many
important antiviral immune response related functions were not significantly enriched for our
samples but were enriched for the lung (GSE147507), and Calu-3 cells (GSE148729)
samples; these processes are- autophagy, apoptotic signaling pathway, interleukin-6 mediated
signaling pathway, interleukin-12 mediated signaling pathway, cytokine-mediated signaling
pathway, inflammatory response etc. (Figure 4B). Moreover, processes like- response to
hypoxia, response to vitamin-D, and lung development were also not enriched for the
deregulated genes of our nasal samples (Figure 4B).

We noticed several commonly enriched important immune signaling pathways for most of
the samples used for the comparison (Figure 4C-D), such as adaptive immune system, innate
immune system, interferon signaling, apoptosis, Toll-like receptor signaling pathway
regulation, antigen processing and presentation, integrin signaling pathway, RIG-I like
receptor signaling pathway, phagosomes etc. (Figure 4C-D, Supplementary Figure 3);
however, pathways like JAK-STAT signaling pathway, Natural killer cell mediated
cytotoxicity, NF-κB signaling pathway, asthma, PI3K-Akt pathway, cellular response to
hypoxia, inflammasomes, and inflammatory response pathway etc. (Figure 4C-D,
Supplementary Figure 3) were not enriched for the deregulated genes of our nasopharyngeal
samples. These results suggest that host responses observed in nasopharyngeal samples have
a different host response compared to the other infection systems. Therefore, to unveil the
mystery behind this observation, we further analyzed these data to compare the gene
expression patterns in different specific functionalities.

Significant gene expression differences were spotted between the nasopharyngeal samples and lung biopsy samples

We compared the normalized read counts of each sample without integrating the respective
controls to shed insights on the differences in gene expression patterns between the individual
samples and tissues. A constant standard deviation was observed for the normalized read
counts of the infected samples (Figure 5A) indicating the acceptability of the normalized
reads for analysis. From the sample to sample distance clustering, principal component
analysis, and clustered heatmap of the count matrix with top 50 genes, we observed that gene
expression profiles of our nasopharyngeal samples are more relevant to that of lung samples;
whereas, high level of variance was observed between the gene expression counts of the cell

lines and primary nasopharyngeal samples (Figure 5B-D). Furthermore, we had a similar

observation from the clustered normalized read counts of the samples based on Pearson's

correlation distance with all genes that vary across samples (Figure 5E). We then narrowed

down our searches to the sample level gene expression profiles of several COVID-19 related

important biological functions within these samples (Figure 6), to understand the gene

expression similarities and dissimilarities among these infections systems, specially

comparing nasal and lung tissues.

Genes related to integrins and integrin signaling pathway are highly

expressed in lung samples compared to the nasopharyngeal samples

Several previous reports suggested an important aspect of integrins in SARS-CoV-2

pathogenesis, therefore, we sought to find out the expression profiles of integrin related genes

in different COVID-19 infection models at sample level [63, 64]. RGD motif of the spike

protein of SARS-CoV-2 can bind the integrins and this motif is placed near to the ACE2-

receptor binding motif [63]. Moreover, evidence of integrin domain binding was also

reported for SARS-CoV [65]. Therefore, we sought to discover the expression profiles of the

integrin related genes in different SARS-CoV-2 infection models. To accomplish this, we

filtered out the integrin and integrin signaling related genes (Supplementary file 6) within the

terms of the GOBP, KEGG pathway, and Bioplanet pathway modules that we used for

enrichment analysis. Intriguingly, we observed that the genes related to integrins and integrin

signaling were highly expressed in analyzed lung samples, and the lowest number of these

genes were expressed in the nasopharyngeal samples (Figure 6A-B, Supplementary Figure

4A). Based on these observations, we can assume that overexpression of integrins and

integrin signaling related genes in the lungs might provide the virus a competitive edge in

invading the lung cells more efficiently compared to the cells of the nasopharynx and

respiratory tracts.

Cytokine and inflammatory signaling genes are overexpressed in lung

samples

Aberrant cytokine stimulation and inflammatory responses are thought to be the major

contributor to pathogenic lung damages in severely affected COVID-19 patients [66, 67]. We

wanted to find out whether the genes related to cytokine signaling and inflammation have

differential expression profiles in lung cells compared to the other infection systems. We

extracted and compared the gene expression values of the genes related to these two terms (Supplementary file 6). We are not surprised to observe that the genes of these two major contributing events of COVID-19 lung pathobiology are significantly overexpressed in lung samples compared to the rest of the SARS-CoV-2 infected cell types (Figure 6C-F, Supplementary Figure 4B-C). Particularly, the analyzed nasopharyngeal samples have very low expression values for the cytokine and inflammatory signaling genes (Figure 6C-F). Therefore, these observations are fueling the preexisting supposition of the roles of enhanced cytokine, and inflammatory signaling for worsening the disease condition in patients with SARS-CoV-2 infected lungs.

A differential gene expression profile was detected for the SARS-CoV-2 entry receptors/associated proteins in different infection models

Expression of receptor protein ACE2 and entry associated proteins such as- TMPRSS2, BSG, CTSL, DPP4 on the cell surface of the host is essential for the invasion of SARS-CoV-2 [62]. Moreover, ACE2 overexpression is thought to increase the infection potentiality of SARS-CoV-2 [68]. Furthermore, Kuba et al. demonstrated the potential role of ACE2 in SARS-CoV induced lung injury [69]. So, we ventured to check the gene expression levels of ACE2 and the other entry associated proteins in the different SARS-CoV-2 infected cells. Surprisingly, we observed that the *ACE2* gene is not expressed in high levels in lung samples as speculated (Figure 6G). However, gene expression levels of the other entry associated proteins were higher in lung samples (Figure 6G). Nonetheless, in few of the lung samples, the *TMPRSS2* gene was not expressed in higher amounts (Figure 6G). Interestingly, we have not detected any expression of *DPP4* gene within the Bangladeshi nasopharyngeal samples (Figure 6G).

Inflammatory immune responses were several folds higher in lungs than the nasopharynx of COVID-19 patients

From our previous observations, it was evident that COVID-19 patient's lung responds to the viral infection differently compared to the epithelial cells of nasopharynx. We then sought to figure out the specific genes and biological functions/signaling pathways which have this differential pattern. We achieved this by designing a multifactorial differential gene expression analysis using a generalized linear model (GLM) [44]; in which we compared the fold changes of every differentially expressed gene in nasopharyngeal and lung (GSE150316)

samples, to discover how many folds lung is alternatively expressing the genes than

nasopharynx in COVID-19.

Firstly, we analyzed the suitability of the data for this design and observed no irregularities

between the data used (Figure 7A-D). Moreover, upon this multifactorial differential gene

expression analysis, we observed an acceptable common biological coefficient of variation;

this variation decreases significantly as the expression values increases (Figure 7E). From the

MA plot, we observed a very high amount of the significantly (p-value < 0.05) several fold

upregulated and downregulated genes in lungs compared to nasopharyngeal samples (Figure

7F). We detected 807 upregulated and 298 downregulated genes in lungs compared to the

nasopharyngeal samples (Supplementary file 7). Interestingly, we noticed the highly

upregulated integrin and integrin signaling genes in lungs compared to the nasal samples

(Figure 7G) which are consistent with our previous observations. Modulatory roles of

integrins are well established in acute lung damages [70]. Similarly, aberrant expression of

genes involved in integrin signaling can also provoke acute lung injuries, namely- *ADAM15*

[71], *SDC1* [72], *CD14* [73], *CD47* [74], *CD9* [75], *HMGB1* [76], *ITA6* [77], and *ITAV* [78]

etc. Therefore, SARS-CoV-2 infection induced deregulation of these genes might be

contributing towards the worsening of the normal pathobiology and functionality of lungs in

COVID-19.

We then performed functional enrichment analysis to hunt down the signaling pathways

which are differentially expressed in lungs compared to the nasopharyngeal cells. These

enrichment analyses revealed that biological functions such as viral process, antigen

processing, and presentation etc. are highly upregulated, function such as- regulation of gene

silencing by miRNA is found downregulated in lungs compared to the nasopharyngeal cells

(Figure 8A). Furthermore, pathways that provide antiviral immunity such as apoptosis,

phagosome, antigen processing and presentation, adaptive immune system, innate immune

system, interferon signaling, different interleukin signaling, cytokine signaling in immune

system etc. were highly upregulated in lungs compared to the nasopharyngeal samples

(Figure 8B-D). Despite having the antiviral protective roles, hyperactivity from these

pathways can significantly worsen the COVID-19 patient's overall lung functionality which

can be further complicated with progressive and permanent lung damage.

Previously, it was reported that transcription factors can contribute to many inflammatory

lung diseases [79, 80] which have similar lung characteristics observed in COVID-19. In this

context, we identified the highly expressed transcription factors in lungs by comparing their respective expression values in nasopharyngeal samples (Figure 8E). Among these, transcription factors such as- CBP [79], CEBP [81], NFAT [79], ATF3 [82], GATA6 [83], HDAC2 [84], TCF12 [85] etc. have significant roles in lung's overall functionality, acute lung injury and antiviral response mechanism in lungs.

SARS-CoV-2 integrates its proteins in regulating the host antiviral immune responses

As we have observed the differential host responses in COVID-19 nasopharyngeal samples, then we sought to interconnect the virus-host interplay in those host responses. We first analyzed how many of the virus interacting host proteins' genes reported by Gordon et al. [21] are differentially expressed in our reported nasopharyngeal samples. Only 51 genes of those proteins are found deregulated in our nasopharyngeal samples (Figure 9A). We then constructed a network interlinking the virus-host protein-protein interaction data from Gordon et al. [21] along with the deregulated genes from the nasopharyngeal samples (Figure 9B). Strikingly, we observed that most of the immune signaling related downregulated genes are directly or indirectly connected to the viral proteins (Figure 9B); this suggests the probable roles of the virus in the differential host responses in the COVID-19 affected patients.

Furthermore, we sought to establish the links between the viral proteins with integrin signaling associated genes by constructing a functional network with the viral-host protein-protein interaction data with the highly upregulated genes observed in lungs (from the comparison analysis between the lung and nasopharyngeal samples) (Figure 9C). From this constructed network, we observed that viral proteins such as ORF10, N, ORF9b, NSP7, NSP15, NSP5, M, NSP13, NSP2, NSP9, ORF8, ORF9c, NSP12, and NSP1 can directly or indirectly interact with the differentially expressed genes in lungs (Figure 9C), suggesting the putative mechanism behind the deregulated integrin signaling to promote the viral invasion in lungs.

Discussion

For a better understanding of the host-virus interaction in the SARS-CoV-2 pathogenesis, transcriptional responses of hosts play an enormous role. Moreover, population-specific disease induced host transcriptome might also correlate the susceptibility from COVID-19

with an individual's ethnicity [86]. In this context, we aimed to discover the representative

host transcriptome response upon SARS-CoV-2 infection by performing and analyzing total

RNA-seq from the nasopharyngeal samples of four COVID-19 positive Bangladeshi

individuals. Also, we analyzed the genomic variations of the SARS-CoV-2 isolates from

these patients to gain more insights into their probable origin. Moreover, we compared the

transcriptome from different SARS-CoV-2 infection models, particularly, we compared the

differential gene expression of the lung biopsy samples with the nasopharyngeal samples of

ours to illustrate the possible molecular mechanisms behind the lung damages in severe

COVID-19 patients.

Analyzing the variations within the sequenced isolates, we observed a very low frequency of

missense amino acid variations within the proteins of SARS-CoV-2, particularly in the spike

and ORF3a gene regions. Many concepts are there correlating the probable roles of variations

with the COVID-19 disease severity [87, 88]. We did not observe any such variations within

the spike region of our reported isolates; however, we recorded an unusual amount of 3'-UTR

and 5'-UTR variations within these four isolates. Surprisingly, we spotted a very rare A>G

mutation at position 10329 of ORF1ab gene in three of our four isolates; we also got another

rare A>T variation at position 25505 of ORF3a gene in one of our isolates. Both of these

variations are extremely rare amongst the other worldwide isolates (Table 1).

Phylogenetic analyses from Nextstrain portal suggested that our reported isolates are closely

related to the Middle East Asian SARS-CoV-2 isolates; which is also very evident from our

constructed neighbor-joining phylogenetic tree of 145 Bangladeshi isolates as our reported

isolates are distinctly placed within the tree. This supports the idea of probable source of

origin of these isolates from Middle-East Asia, while the rest of the Bangladeshi isolates are

more related to the European isolates. As our isolates were obtained from the Chittagong area

of Bangladesh, from where a large number of people recently immigrated to Middle-East

(particularly Saudi Arabia) for work [89]; those immigrant people returning from the Middle-

East during this pandemic might have brought these isolates into Bangladesh.

Previously, host transcriptional responses reported by Blanco-melo et al. [24] and Butler et al.

[25] suggested a potential increase in the host antiviral immune responses such as- interferon

signaling, interferon stimulated gene signaling, chemokine signaling, cytokine signaling etc.;

however, Blanco-melo et al [90] also reported the presence of low IFN-I and IFN-III in

COVID-19 patient's lung cells. We observed similar host immune responses, interferon, and

cytokine signaling in Bangladeshi COVID-19 patients too. Moreover, we also observed a
stimulated innate immune response in our patients which was also reported for other COVID-
19 patients [91].

Astoundingly, important signaling pathways those elicit antiviral immune responses such as-
apoptosis [20], phagosome formation [92], antigen processing and presentation [93], Natural
killer cell mediated cytotoxicity [94], and Toll-like receptor signaling [95] etc. were found
downregulated in Bangladeshi COVID-19 patients. Also, pathways such as- HIF-1 response
[96], PI3K-Akt signaling [97], and IL-17 signaling [98] etc. are also found deregulated which
could assist the COVID-19 patients suffering from hypoxia, lung injury, and inflammation of
the respiratory tract.

While we were comparing the nasopharyngeal cell's transcriptional responses with other
SARS-CoV-2 infection models, we observed that lung cells elicited the immense cytokine
and inflammatory responses against the invading viral pathogen. These overstimulated
responses sometimes can do irreversible damages to the lungs [99]. This might shed insights
into the COVID-19 disease severity when the viral infection progresses into the lungs.

Though an increased amount of ACE2 will facilitate the invasion of SARS-CoV-2,
nonetheless, we observed a significant downregulation of ACE2 in lung cells. This
phenomenon could backup the concept of ACE2 downregulation by SARS-CoV-2 itself after
using it [100], thus reducing the organ protective roles of ACE2 [101] and resulting in
progressive lung damages.

Integrins were reported important for the entry of SARS-CoV into the host cells [65], so it
was speculated similar phenomenon might also be present in SARS-CoV-2. This idea is
further intensified after the study by Sigrist et al. [63], who suggested the presence of an
integrin-binding RGD motif in the spike of SARS-CoV-2. Surprisingly, upon the gene
expression comparison between the different SARS-CoV-2 infected cells, we observed
several folds upregulated expressions of genes related to the integrin signaling pathway in
lung cells. This observation could support the idea of increased viral infections in lungs might
be happening due to the overexpression of these probable attachment proteins. Also, the
network analysis suggests a probable mechanism of upregulation of these proteins by the
virus itself by the putative interactions through its proteins. Though more targeted studies
should be undertaken for conclusive evidence supporting this phenomenon.

Conclusion

In this study, we present the very first report of the host transcriptional response data from COVID-19 patients of the South-Asian region along with the SARS-CoV-2 isolates obtained from these patients. This data might provide newer insights into the host susceptibility from the perspective of ethnicity as well as will provide newer aspects of host responses against the virus in the different parts of the respiratory tract. However, a limited number of patient data is used here, but subsequent incorporation of more patient data from other parts of the world will significantly increase the understanding of this complex host-virus response in COVID-19, which will help in designing therapeutic interventions as well as in current clinical management of the patients.

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Competing Interests

The authors declare no competing interests.

Author Contributions

ABMMKI designed the workflow and conceived the project. AMAMZS performed sample collection and detection. RA, MSH, SMTK, and MSI performed the RNA sequencing and viral genome assembly. ABMMKI and MAAKK performed the RNA-seq data analysis, comparative genomics, and other bioinformatic analyses. MAAKK and ABMMKI wrote the manuscript. All authors read and approved the final manuscript. ABMMKI and MAAKK contributed equally to this work.

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Data Availability

SARS-CoV-2 genomes are deposited at GISAID initiatives portal (https://www.gisaid.org/) with accessions- EPI_ISL_450340, EPI_ISL_450341, EPI_ISL_450342, EPI_ISL_450345.

585 Raw RNA-seq data are deposited at NCBI-GEO (https://www.ncbi.nlm.nih.gov/geo/) under
586 the accession- GSM4667504, GSM4667505, GSM4667506, GSM4667507. Additionally,
587 publicly available data were utilized (Supplementary file 1). Analyses generated data are
588 deposited as supplementary files.

Ethics statements

590 Patients' written-consents were taken before the collection of the samples.

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List of Tables

Table 1: Observed variations within the four Bangladeshi SARS-CoV-2 isolates reported in this study.

Genomic position: Variation	Variation Type	Associated genomic region	Protein: amino acid change	Frequency in the four isolates used in this study	Frequency in the other Bangladeshi isolates	Frequency in the isolates from rest of the world
1: ATTAAAGGTTTA>-	Intergenic variant	5'UTR	-	1	-	-
1: ATTAAAGGTTTATA>-	Intergenic variant	5'UTR	-	1	-	-
2: T>TA	Intergenic variant	5'UTR	-	1	0	0
2: T>TTTCAAAGATCAAGTCA	Intergenic variant	5'UTR	-	1	0	0
4: A>T	Intergenic variant	5'UTR	-	1	0	58
7: G>C	Intergenic variant	5'UTR	-	1	0	16
9: T>TTTTCGC	Intergenic	5'UTR	-	1	0	0

Genomic position: Variation	Variation Type	Associated genomic region	Protein : amino acid change	Frequency in the four isolates used in this study	Frequency in the other Bangladeshi isolates	Frequency in the isolates from rest of the world
	variant					
12: A>T	Intergenic variant	5'UTR	-	1	0	22
13: T>C	Intergenic variant	5'UTR	-	1	0	36
280: C>T	Synonymous variant	orf1ab	5V	1	0	5
601: C>T	Synonymous variant	orf1ab	112G	1	1	6
8782: C>T	Synonymous variant	orf1ab	2839S	4	1	3012
10323: A>G	Missense variant	orf1ab	3353K>R	1	5	154
10329: A>G	Missense variant	orf1ab	3355D>G	3	1	1
10870: G>T	Synonymous variant	orf1ab	3535L	1	0	27
12119: C>T	Missense variant	orf1ab	3952P>S	1	0	8
15324: C>T	Synonymous variant	orf1ab	5020N	3	5	818
19414: G>A	Missense variant	orf1ab	6384V>I	1	0	0
22468: G>T	Synonymous variant	S	302T	4	1	99
23320: C>T	Synonymous variant	S	586D	1	0	2
25505: A>T	Missense variant	ORF3a	38Q>L	1	0	2
28087: C>T	Missense variant	ORF8	65A>V	1	0	23
28144: T>C	Missense	ORF8	84L>S	4	1	3050

Genomic position: Variation	Variation Type	Associated genomic region	Protein : amino acid change	Frequency in the four isolates used in this study	Frequency in the other Bangladeshi isolates	Frequency in the isolates from rest of the world
	variant					
28878: G>A	Missense variant	N	202S>N	4	1	253
29392: G>T	Missense variant	N	373K>N	2	2	6
29742: G>A	Downstream gene variant	3'UTR	-	4	1	21
29856: T>A	Intergenic variant	3'UTR	-	1	0	6
29858: T>A	Intergenic variant	3'UTR	-	1	0	5
29864: GAATGACAAAAAAAAAAAAAAAAAAAAAA>G	Intergenic variant	3'UTR	-	1	0	0
29864: GAATGACAAAAAAAAAAAAAAAAAAAAAAAA>T	Intergenic variant	3'UTR	-	1	0	0
29870: CAAAAAAAAAAAAAAAAAAAAAAAAAAA>C	Intergenic variant	3'UTR	-	1	1	-
29870: C>G	Intergenic variant	3'UTR	-	1	0	3
29872: A>T	Intergenic variant	3'UTR	-	1	0	12
29873: A>C	Intergenic variant	3'UTR	-	1	0	3
29874: A>G	Intergenic variant	3'UTR	-	1	0	12
29875: A>G	Intergenic variant	3'UTR	-	1	1	5
29878: A>T	Intergenic	3'UTR	-	1	0	3

Genomic position: Variation	Variation Type	Associated genomic region	Protein : amino acid change	Frequency in the four isolates used in this study	Frequency in the other Bangladeshi isolates	Frequency in the isolates from rest of the world
	variant					
29880: A>G	Intergenic variant	3'UTR	-	1	2	5
29882: A>G	Intergenic variant	3'UTR	-	1	0	13
29883: A>T	Intergenic variant	3'UTR	-	1	0	8
29884: A>C	Intergenic variant	3'UTR	-	1	0	10
29885: A>G	Intergenic variant	3'UTR	-	1	1	11
29886: A>T	Intergenic variant	3'UTR	-	1	1	5
29887: A>G	Intergenic variant	3'UTR	-	1	0	11
29888: A>T	Intergenic variant	3'UTR	-	1	1	4
29890: A>G	Intergenic variant	3'UTR	-	1	1	6
29891: A>G	Intergenic variant	3'UTR	-	1	0	15
29892: A>G	Intergenic variant	3'UTR	-	1	0	13
29893: A>G	Intergenic variant	3'UTR	-	1	0	15
29895: A>T	Intergenic variant	3'UTR	-	2	0	6
29896: A>G	Intergenic variant	3'UTR	-	1	0	7
29896: A>C	Intergenic variant	3'UTR	-	1	0	3
29897: A>G	Intergenic	3'UTR	-	2	0	4

Genomic position: Variation	Variation Type	Associated genomic region	Protein : amino acid change	Frequency in the four isolates used in this study	Frequency in the other Bangladeshi isolates	Frequency in the isolates from rest of the world
	variant					
29898: A>G	Intergenic variant	3'UTR	-	2	0	6
29898: A>T	Intergenic variant	3'UTR	-	1	0	5
29900: A>G	Intergenic variant	3'UTR	-	1	0	10
29901: AAA>A	Intergenic variant	3'UTR	-	1	0	-
29901: A>G	Intergenic variant	3'UTR	-	2	0	5
29903: A>GCCGTCGT	Intergenic variant	3'UTR	-	1	0	-
29903: A>GCGTCGTGT	Intergenic variant	3'UTR	-	1	0	-

Figure Legends

Figure 1: Genomic information of the sequenced SARS-CoV-2 isolates. **A.** Genome coverage normalized density map for the four sequenced SARS-CoV-2 isolates. **B.** Pie-chart illustrating the different types of variations found within these four isolates. **C.** Genome location-wise representation of the mutations and their associated frequency. **D.** Isolate-wise variation information. **E.** Gene-wise amount and type of mutations. **F.** Annotated impacts of the different mutations (only those are shown which have frequencies more than 1). **G.** Frequencies of selected unique mutations observed in these isolates.

Figure 2: Phylogenetic tree of Bangladeshi SARS-CoV-2 isolates. Neighbor-joining tree using MEGA tools. Isolates reported in this study are indicated with a red arrow. The evolutionary history was inferred using the Neighbor-Joining method. The optimal tree with the sum of branch length = 0.01403419 is shown. The percentage of replicate trees in which the associated taxa clustered together in the bootstrap test (500 replicates) are shown next to

the branches. The evolutionary distances were computed using the Maximum Composite
Likelihood method and are in the units of the number of base substitutions per site. This
analysis involved 145 nucleotide sequences. Codon positions included were
1st+2nd+3rd+Noncoding. All positions with less than 95% site coverage were eliminated,
i.e., fewer than 5% alignment gaps, missing data, and ambiguous bases were allowed at any
position (partial deletion option). There was a total of 29827 positions in the final dataset.
Values represent bootstrap numbers (%).

Figure 3: A. Variance plot. This plots the standard deviation of the transformed data, across
samples, against the mean, using the variance stabilizing transformation. The vertical axis in
the plots is the square root of the variance over all samples. **B.** Sample to sample distance
plot. A heatmap of distance matrix providing an overview of similarities and dissimilarities
between samples. Clustering is based on the distances between the rows/columns of the
distance matrix. **C.** Principal component analysis plot. Samples are in the 2D plane spanned
by their first two principal components. **D.** Clustered heatmap of the $\log_2$ converted
normalized count matrix RNA-seq reads, top 50 genes, of nasopharyngeal samples. **E.**
Normalized $\log_2$ read counts of the genes encoding SARS-CoV-2 receptor and entry
associated proteins. Enrichment analysis and comparison between deregulated genes and the
genes of some selected processes in SARS-CoV-2 infected nasopharyngeal samples and
SARS-CoV-2 infected lung biopsy samples using **F.** GOBP module, **G.** KEGG pathway, **H.**
Bioplanet pathway module. Selected significant terms are represented in heatmaps.
Significance of enrichment in terms of the adjusted p-value (< 0.05) is represented in color-
coded P-value scale for all heatmaps; Color towards red indicates higher significance and
color towards yellow indicates less significance, while grey means non-significant.
Normalized $\log_2$ converted read counts are considered as the expression values of the genes
and represented in a color-coded scale; Color towards red indicating higher expression, while
color towards green indicating little to no expression.

Figure 4: Comparison of the gene expression patterns in different SARS-CoV-2 infection
models. **A.** Venn-diagram showing the observed deregulated genes (with their respective
control) in the different cell types. Enrichment analysis and comparison between deregulated
genes in different SARS-CoV-2 infection models using **B.** GOBP module, **C.** Bioplanet
pathway module, **D.** KEGG pathway module. Selected significant terms are represented in
heatmaps. Color scale/schemes are similar to Figure 3.

Figure 5: A. Variance plot, **B.** Sample to sample distance plot, **C.** Principal component

analysis plot, **D.** Clustered heatmap of the count matrix of the normalized RNA-seq reads of

different SARS-CoV-2 infection samples using to 50 genes. **E.** Gene expression heatmap

showing global gene expression profiles in the individual infected samples of the various

infection system. Heatmap is clustered based on Pearson's distance with genes that vary

across the sample, leaving out genes that do not vary significantly.

Figure 6: Heatmaps representing the sample level absolute expression of Integrin related

genes **A.** across the different SARS-CoV-2 infection models, **B.** in only nasopharyngeal

samples and lung samples; Cytokine signaling related genes **C.** across the different SARS-

CoV-2 infection models, **D.** in only nasopharyngeal samples and lung samples; and

Inflammation related genes **E.** across the different SARS-CoV-2 infection models, **F.** in only

nasopharyngeal samples and lung samples; **G.** Expression profiles of genes encoding SARS-

CoV-2 receptor and entry associated proteins. Normalized (DESeq2) Log_2 converted read

counts are considered as the expression values of the genes and represented in a color-coded

scale; Color towards red indicating higher expression, while color towards green indicating

little to no expression.

Figure 7: A. Variance plot, **B.** Sample to sample distance plot, **C.** Principal component

analysis plot, **D.** Clustered heatmap of the count matrix of the normalized RNA-seq reads

(top 50 genes) of the SARS-CoV-2 infected nasopharyngeal and lung samples. **E.** Common

dispersion plot or the biological coefficient of variation plot. Here we are estimating the

dispersion. The square root of the common dispersion gives the coefficient of variation of

biological variation. Here the coefficient of biological variation is around 0.8. **F.** MA plot.

Plot log-fold change against log-counts per million, with DE genes are highlighted. The blue

lines indicate 2-fold changes. Red and blue points indicate genes with P-value less than 0.05.

G. Expression profiles of genes encoding Integrins. Log_2 (fold change) values are considered

as the expression values of the genes and represented in a color-coded scale; Color towards

red indicating higher expression, while color towards green indicating little to no expression.

Figure 8: Enrichment analysis and comparison between deregulated genes and the genes of

some selected processes in SARS-CoV-2 infected nasopharyngeal samples versus SARS-

CoV-2 infected lung biopsy samples using **A.** GOBP module, **B.** KEGG pathway, **C.**

Bioplanet pathway module, **D.** Reactome pathway module. Selected significant terms are

represented in heatmaps. Color schemes are similar to Figure 3. For individual processes,

blue means presence (significantly differentially expressed gene) while grey means absence (not significantly differentially expressed genes for this module for this experimental condition).

Figure 9: A. Venn diagram showing the commonly deregulated genes between deregulated genes in our nasopharyngeal samples and Gordon et al. reported viral protein-interacting high confidence host proteins. Network representing the interactions between genes in **B.** Deregulated genes in Bangladeshi nasopharyngeal samples along with SARS-CoV-2 proteins and Gordon et al. described viral interacting host proteins, and **C.** Differentially expressed Integrin related genes in lungs compared to the nasal samples along with SARS-CoV-2 proteins and Gordon et al. described viral interacting host proteins. Hexagon, ellipse, rounded rectangle represents viral proteins, process-related genes, and proteins that interact with viral proteins, respectively. Expression values of the genes and represented in a color-coded scale. Color towards red indicating higher expression, while color towards green indicating little to no expression.

Supplementary Figure Legends

Supplementary Figure 1: Snapshot of Nextstrain data portal showing the phylogenetic relationship of two SARS-CoV-2 isolates used in this study. Isolates of this study are indicated using a red arrow.

Supplementary Figure 2: Deregulated genes of selected terms from Figure 3 in different SARS-CoV-2 infection systems. Genes of selected significant terms are represented here. For individual processes, blue means presence (differentially expressed gene of the module term) while grey means absence (not differentially expressed in the experimental condition in that module term). Processes in the green, blue, red color background represent KEGG, Bioplanet, GOBP enriched terms, respectively.

Supplementary Figure 3: Deregulated genes of selected terms from Figure 3 in different SARS-CoV-2 infection systems. For individual processes, blue means presence (differentially expressed gene of the module term) while grey means absence (not differentially expressed in the experimental condition in that module term). Processes in the green, blue, red color background represent KEGG, Bioplanet, GOBP enriched terms, respectively.

Supplementary Figure 4: Expanded view of the heatmaps A, B, C of Figure 6.

List of supplementary files

Supplementary file 1: Sources of the data used in this study.

Supplementary file 2: Per base sequence quality reports of the generated RNA-seq reads of the four COVID-19 infected nasal samples used in this study.

Supplementary file 3: Isolate-wise variation information of the four SARS-CoV-2 isolates used in this study.

Supplementary file 4: Differentially expressed genes found in the four Nasal samples of Bangladeshi COVID-19 patient.

Supplementary file 5: Differentially expressed genes in different SARS-CoV-2 infected cell types.

Supplementary file 6: Genes and associated terms used for filtering the expression values used in Figure 6.

Supplementary file 7: Differentially expressed genes in SARS-CoV-2 infected Lungs compared to the Bangladeshi Nasal samples used in this study.

A

SARS-CoV-2 Interacting
Host Proteins

Differentially expressed genes
in Nasopharyngeal samples

281
(14.8%)

51
(2.7%)

1563
(82.5%)

B

Log₂ (Fold change) scale

-3   0   3

C