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Exploring the Impact of COVID-19 on Aircraft Boarding Strategies Using Discrete Event Simulation

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ABSTRACT

Aviation is one of the most severely impacted industries by COVID-19. The passenger boarding-process is not only a bottleneck but is also one of the riskiest processes for COVID-19 transmission. There is a need for a decision-support tool that can proactively test the impact of COVID-19 policies on the passenger boarding-process. We achieve this by developing an adaptable modeling approach to Discrete Event Simulation (DES) that simulates the process of boarding under different COVID-19 policies and boarding-strategies. DES model was created using time and motion studies, flightlogs and manuals. Programing-logic was created using n=29 subject-matter experts. As a demonstrator-case, we tested seven of the most common boarding-strategies under different COVID-19 stages: pre-COVID, COVID-19 stage 1 and 2. Preliminary-results show the COVID-19 transmission risk may be decreased with a trade-off: passenger-satisfaction may decrease due to an increase in boarding-time and waiting-time. Steffen's method was most-effective in minimizing COVID-19 risk but is the most difficult to implement. Reverse pyramid and Window Middle Aisle, while slightly less effective than Steffen's method, but overall, more-effective and easier to implement with minimal COVID-19 risk. For COVID-19 stage 1 and 2, boarding time increased up to 33% and 64%, respectively, in-comparison to baseline pre-pandemic conditions. Further, up to 1.5 and 6.6 seat and aisle interferences along with a jetway-seat time of up to 13 minutes were observed. The developed modeling approach serves as a direct response to ICAO's (International Civil Aviation Organization) need for a tool to proactively test and develop policies that minimize COVID-19 risk.

Keywords: airport operations, COVID-19 flying restrictions, passenger satisfaction, aircraft boarding, passenger health risk

1. INTRODUCTION

Airlines generate most of their revenue while flying. In the United States alone, delays in aircraft departure cost $29 billion to the airline industry and $17 billion to passengers (Ball *et al.*, 2010; Milne *et al.*, 2018). Therefore, it is imperative to reduce the turnaround time and maximize the number of flights. When the aircraft lands, there are a number of operations that need to be performed before its next departure (Malandri *et al.*, 2019). The longest and most difficult factor to control is the process to board passengers to the aircraft (Jafer and Mi, 2017). Whilst most operations run in parallel, aircraft boarding is often the final and a stand-alone step. Increased boarding time also leads to paying more parking charges (Jaehn and Neumann, 2015). Reductions in boarding time can not only increase profits but will also lead to greater passenger satisfaction (Van Den Briel *et al.*, 2003). It is imperative that advancements are made to decrease turnaround time but newer challenges, such as terrorism, oil crisis, natural disasters, virus outbreaks such as the novel coronavirus (COVID-19) etc., make it difficult to improve operations (Suau-Sanchez *et al.*, 2020).

1.1 The Impact of COVID-19 on Commercial Aviation

The first known infections of COVID-19 were observed around Wuhan (China) in December 2019 *(Sun et al.*, 2021). This disease is caused by SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) and was declared a pandemic by the World Health Organization (2020) on March 11, 2020. Given the airborne transmission nature of the virus (Bazant and Bush, 2021; Tang *et al.*, 2021), several residents have opted to stay in their homes and avoid travel (Lee *et al.*, 2022). The most significant impact of COVID-19 has been observed on the airline industry (Boston Consulting Group, 2020). The International Civil Aviation Organization [ICAO] (2020) has predicted a $385 billion and $132 billion potential loss of gross operating revenues of airlines for international and domestic passenger traffic respectively. Air travel is considered to be of high risk; therefore, airports have seen a drop of 96% of the passenger population amidst the COVID-19 pandemic (CNN, 2020a). Given the less demands, there are now reduced flights and therefore, little to no profit is observed. As a result, airlines such as Virgin Atlantic have filled for bankruptcy (BBC News, 2020b; CNN, 2020b; Forbes, 2021). In response to decreased demands, Emirates, the world's biggest long-haul carrier, laid off 9000+ workers (Gulf News, 2020). In the United States alone, about 1,800 commercial aircrafts have been grounded because of low demand (CNN, 2020a). Before COVID-19, the most significant impact on air travel from a virus outbreak was for the 2003 SARS outbreak. Provisional recovery of COVID-19 has found to be immensely slow in comparison to previous SARS outbreak economic recessions (Suau-Sanchez *et al.*, 2020). The increase in vaccination rates has brought an increase in air travel (Airports Council International, 2021; Lusiantoro *et al.*, 2022). However, the perception of infection risk during air travel is still one of the strongest factors of reviving the air travel industry *(Khatib, et al., 2021; Meng et al.*, 2021).

The International Air Transport Association (IATA), representing 300+ global airlines, implores the dire need for commercial aviation processes to be adapted in response to COVID-19 (Peskett, 2020). IATA (2020a) has recommended steps to protect flight workers and passengers from the infection include mandatory temperature checks before departure, wearing face masks and social distancing. Most airline workers and passengers are becoming increasingly vocal in demanding commercial airliners to do more than just providing basic PPE. (Seglins *et al.*, 2020). One way to assist is by updating the passenger boarding process – one of the riskiest parts of commercial aviation from COVID-19 virus transmission perspective (BBC News, 2020a). During the boarding process, passengers and crew are often crammed inside small jetways and narrow-body aircraft that have single aisle. Thus, creating more foot traffic, making it high-risk as passengers and crew are unable to maintain safe distance and have to move forward and back. Unlike airport terminals where everyone can observe safe distancing (BBC News, 2020a). Therefore, a tool is needed that can allow commercial airliners to test boarding strategies that take into account the potential COVID-19 impact and passenger population, rather than just trial and error. Using computerized simulation tools such as Discrete Event Simulation (DES), we may be able to help achieve this (Kierzkowski and Kisiel, 2020; Van Landeghem and Beuselinck, 2002).

1.2 Aim

The aim of this paper is to develop a passenger focused approach to simulation that simulates the process of passenger boarding to quantify the impact of different COVID-19 policies on passenger satisfaction and passenger health risk. The emphasis here is on the development of an adaptable model rather than a definitive answer. So that commercial airliners, policy makers and other aviation stakeholders can proactively test the impact of further changing operational design and technical policies. This study is a response to IATA's need for developing tools to assess and adapt aviation processes to COVID-19 pandemic restrictions (IATA, 2020a; Peskett, 2020).

1.3 Related Work

In the past, several researchers have used simulation to model the boarding process. One of the first simulation models can be traced back to Boeing when they created a 'passenger enplane/deplane' simulation model where they tested different interior layout and on different boarding strategies (Marelli *et al.*,1998). Van Landeghem *et al.* (2002) used DES to illustrate detailed structures of the boarding problem, highlighting simulation can be used to ramp-up the boarding process. Ferrari and Nagel (2005) used cellular simulation technologies to test early and late passengers and occupancy levels. Bazargan (2007) explored the interferences among the passengers whilst boarding the aircraft. Steffen (2008) used a Markov Chain Monte Carlo algorithm to create an optimal boarding method. While, this method has been very successful but never been implemented because of practical concerns. Steiner and Philipp (2009) explored the addition of a pre-boarding area as a means to speed up boarding time. Tang *et al.* (2012) used simulation to assign passenger seats based on passenger attributes such as walking speed and carry-on luggage. Similarly, Milne and Kelly (2014) assigned passenger seats based on carry-on luggage that would be evenly distributed throughout the aircraft. While, these techniques (Milne and Kelly, 2014; Tang *et al.*, 2012), may be effective but these were harder to implement as that would mean seat numbers are assigned once all check-in is done. There by, increasing boarding time. Qiang *et al.* (2014) used cellular automation simulation to explore reduce boarding time by accounting for passenger specific properties, such as luggage. Fuchte (2014) tested aircraft cabin modification to improve the boarding efficiency. Ching-Chung (2015) focused on passenger interferences as a medium to reduce boarding time. Schultz (2017) explored the impact of varying seat interference and infrastructure level on varying aircraft boarding process. Schmidt *et al.* (2017) tested different seating concepts on single-aisle and twin-aisle aircrafts. Kierzkowski and Kisiel (2017) studied occupancy levels and interferences in low-cost carriers. Schultz and Schmidt (2018) analyzed passenger acceptance of boarding order, arrival rates and seat loading factors, and reported rear-door boarding increases efficiency. Delcea *et al.* (2018) used agent based modeling (ABM) to explore two-door boarding from apron. Schultz and Schmidt (2018) tested the impact of 'slip-slide seat' during passenger interactions while passing through. Wittmann (2019) explored boarding of four sets of passengers while taking into consideration passenger attributes such as speed, luggage etc. Milne, *et. al.* (2020) used ABM to test boarding from apron buses in a two door aircraft, where passengers were assigned to buses depending on their boarding groups. Cotfas, *et. al.* (2020) used ABM to test the impact of different social distancing (1m, 1.5m and 2m) on aircraft boarding in response to COVID-19 restrictions for Airbus 320. While most studies have focused on reducing boarding time (Coppens *et al.*, 2018), none of the studies (to our knowledge) have explored the development of an adaptable approach to quantify the impact of boarding strategies on COVID-19 virus transmission. This study fulfils this gap by developing an adaptable tool to test and quantify the impact of COVID-19 policies in terms of passenger satisfaction and passenger health risk.

2. METHODS

The Virtual Aircraft (VA) Model was created in consultation with subject matter experts (n =29) with up to 35 years experience in the domain of aerospace. The VA model is built on the DES environment software ARENA (Rockwell Automation). DES is an operations management tool that can represent complex structures as a sequence of stochastic events over a discrete set of points (Malandri *et al.*, 2019; Qureshi *et al.*, 2020; Truong *et al.*,2020). DES can be used to assess the efficiency of proposed and existing systems (Günal and Pidd, 2010; Jun *et al.*, 1999; Rajendran and Shulman, 2020). DES has proven to be a successful tool in the realm of manufacturing, aviation and healthcare (Chakraborty, 2020; Fatemi *et al.*, 2008; Iwata and Mavris, 2013; Kierzkowski and Kisiel, 2020; Legato and Mazza, 2001; Perez *et al.*, 2014; Qureshi, *et al.*, 2021; Uvet, 2020).

The VA model imitates the process of boarding passengers in an aircraft under varying technical design and operational policies. Inputs to the model (as illustrated in **figure 1**) include: 'virtual layout', 'passenger boarding group assignment', 'COVID-19 protocols', 'passenger type', 'walking speed', 'passenger compliance', 'passenger delays and last call', 'interference time', 'boarding document inspection', and 'hand carry loading time'. In this study, the VA model quantifies passenger satisfaction and the passenger health risk (**figure 1**). Indicators to passenger satisfaction include: 'cumulative boarding time', 'passenger waiting time (pre-boarding)'. Passenger health risk indicators include: 'jetway-seat time', 'seat interference' and 'aisle interference'.

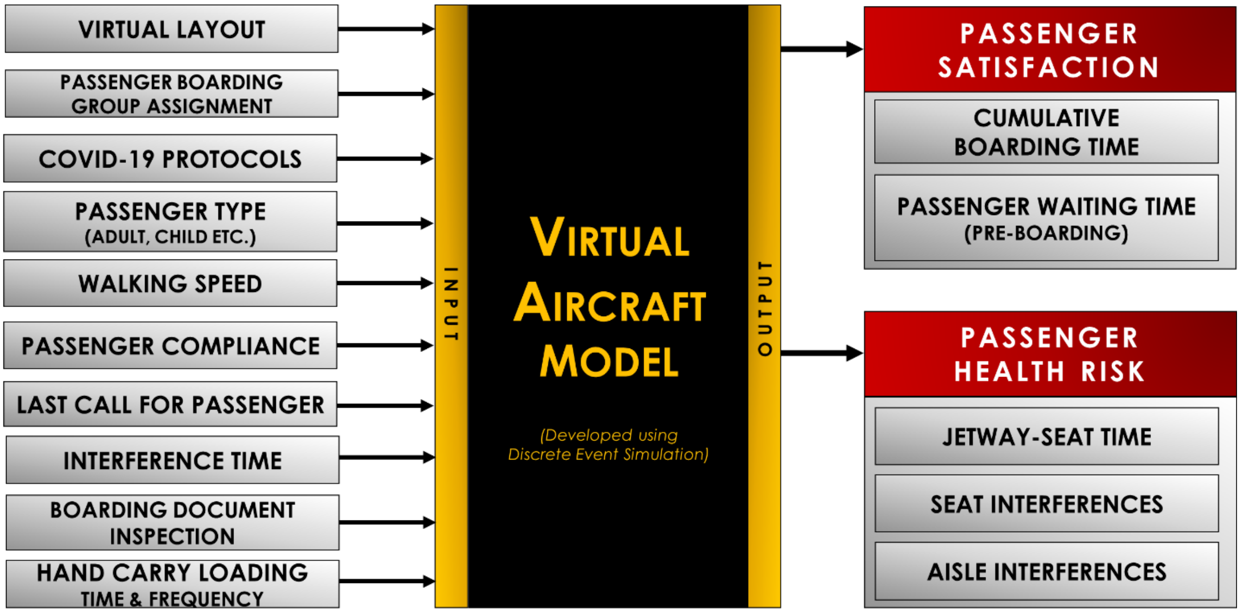

Figure 1 provides an overview of the inputs and outputs programmed in the Virtual Aircraft (VA) model

2.1 Model Inputs

Virtual layout – The physical environment of the aircraft. This reflected the position and total number of seats, the distances between seats and the width and length of the aisle. The virtual layout of the model was created using Visio (Microsoft). In this study, the aircraft resembled a smaller commercial aircraft such as Airbus 320 or Boeing 737, where there are 26 rows each of 6 seats, 2 x (window, center, aisle). The overall layout (inter-seat distance, emergency exit locations and jetway entrance) was created using flight manuals. The emphasis here was to test the process of boarding passengers in an aircraft under varying strategies, rather than a definitive answer for a specific model of an aircraft. The VA model is very adaptable – it can be adapted to creating/testing different aircraft designs.

Passenger boarding group assignment – This is the boarding group assigned to passengers. Based on each boarding strategy, a different boarding group is used. Where, 1 = highest and 5 = lowest.

COVID-19 protocols – The COVID-19 protocols were devised via focus groups with n = 14 SMEs with 6 to 35 years of experience, consisting of senior directors, airport authorities, airport security and immigration officers, and airport managers. These participants belonged to metropolitan area international airports. A consensus approach was used during focus groups. These protocols include: i) *Temperature check time* – The time required to successfully perform a mandatory temperature check. While some countries have mandated a COVID-19 test before 2 or more days before travel. But, passenger temperature checks have now become mandatory across the globe (Government of Canada and Transport Canada, 2020). In the VA model, if a passenger's temperature was found greater than the standard, the passenger was put aside and this task was performed again after a 5-minute delay. ii) *COVID-19 Document Inspection* – The time required to inspect the vaccination documentation (certificate) before boarding. Time and motion studies with n = 20 participants, were used to construct the Temperature check and Vaccine documentation time. iii) *Physical distancing* – The minimum distance that passengers must maintain between each other. The VA model follows the physical distancing of 2mm, as per the recommendation of IATA (Cotfas *et al.*, 2020). iv) *Seating assignment* entails if certain seats should be kept vacant to observe safe distancing. In the demonstrator case (COVID-19 stage 1 only), the middle seats were kept vacant. This is further discussed in Section 2.3.1 (experimental design). The VA model can be adapted to test variations in COVID-19 protocol.

Passenger type – Air travel is not limited a specific passenger type; older adults, adults, children, teens – all travel. Anonymized passenger flight data was taken from 20 domestic and international flights (10 + 10), for the months of August and September. Where, the biggest proportion were adults (69%), followed by teens (16.9%), children (7.2%) and older-adults (5.9%). The smallest population group were infants (1%). The VA model can be easily adapted to test different passenger type distribution for a specific month e.g., December – Holiday travel season or to test an "all teen" or an "all adult" flight.

Walking Speed illustrates the speed of the passenger while moving inside the narrow aisle of the aircraft. Time and motion studies were done with 28 participants (n = 14 adults, n =7 teens, n = 4 children and n = 3 older-adults), to quantify the speed of the passenger for two conditions. 1) Normal operating conditions, 2) COVID-19 conditions, where safe distancing (i.e., 2m a part) was to be observed. These revealed that the passengers were walking slower during COVID-19 conditions in comparison to normal operating conditions.

Passenger compliance constitutes to how well passengers can listen and obey instructions. These included: entering the incorrect boarding group queue, sitting on unassigned seats and incorrect way of storing carry-on luggage, that required rework. Multiple focus groups with SMEs (n = 21), consisting of essential airline staff with 3 to 11 years of experience, participated in the study. A consensus approach was used to quantify compliance level. In addition, the focus group revealed: reduced compliance level negatively impacts walking speed, passenger delays and hand-carry loading time.

Last Call for Passenger – This represents the frequency of passengers who could not board in time as a result a last call announcement was made. The boarding process was left incomplete until they arrived. Historical flight boarding logs (n = 20) were used to calculate the frequency of passenger delays. 'Last Call for Passenger' delays are not always due to compliance issues; Discussions with subject matter experts have revealed this is often due to delays in security and/or immigration stations.

Interference time – The time required for a passenger to vacate their seat, either centre or aisle, to let the other passenger enter that row (either window or center). This was calculated using a time and motion studies with n = 28 participants.

Boarding Document Inspection – Altered procedures now exist globally for boarding document inspection. The passenger passes their passport or other photographic ID along with their boarding pass to the gate agent; they then lower their face mask for the manual facial verification, after keeping a safe distance with the gate agent (US Departments of Transportation *et al.*, 2020). A time and motion study with n= 20 participants were conducted to quantify this time duration.

Hand carry loading time and frequency – The time required for each passenger to store their carry-on bags on the upper head bins. Time and motion studies (n = 28) were done to capture passengers storing their carry-on bags (varying 2kgs to 10kgs) on the overhead bin. The frequency of each passenger having a bag was calculated using Milne and Kelly (2014).

Each of the above-mentioned elements can be easily adapted to specific contexts. The developed VA model demonstrates an adaptable approach that maybe applied to different system designs. The emphasis here was to test the ability to simulate the process of boarding passengers under different operational policies and technical designs, such as COVID-19 phases.

2.2 Model Outputs

The VA model is quantifying passenger satisfaction and passenger health risk.

2.2.1 Passenger Satisfaction

Indicators for passenger satisfaction include: i) *Cumulative Boarding time* – the total time it takes to complete the boarding process. ii) *Passenger waiting time (Pre-boarding)* **–** The average wait time for a passenger before they can enter the jetway. This included temperature and vaccination documentation checks.

2.2.2 Passenger Health Risk

This metric is of concern to the passenger's health and reflects potential exposure to the COVID-19 droplets through air and through surfaces, by passengers who may later touch their mouth or nose. Indicators for passenger health risks include:

i) *Seat interferences* **–** The total instances where a passenger on a center/aisle seat sat down before the passenger on the window/center seat sat down. This health risk stems from interactions between passengers and the surface, e.g. touching the other passenger's armrest and headrest when vacating the seat (to allow the other passenger to sit down in the Window/Middle seat etc.). The COVID-19 virus may spread through air droplets and surfaces as they maybe later touched by the passengers who may touch their noses and mouths.

ii) *Jetway-Seat time* **–** The average time spent by the passenger before they can sit on their assigned seat, from the moment they enter the jetway. A possibly infectious traveller may be walking or standing in the row of seated passengers while waiting in line for a down-aisle passenger to vacate the aisle. Therefore in this context, the longer the duration, the greater the health risk for the passengers (Cotfas *et al.*, 2020).

iii) *Aisle interferences* **–** The total instances where a passenger was forced to wait as the passenger in front of them was loading their baggage on the overhead bin. Increased aisle interferences may create bottlenecks and increase time. Increased exposure time and, seat and aisle interferences, may lead to a greater risk for transmission of COVID-19 virus.

2.3 Experimental Design and Analysis

2.3.1 Experimental conditions

The VA model was run on three different experimental conditions.

i) Pre-COVID-19 era – In this condition, passengers could sit next to one another and did not had to follow safe distancing guidelines.

ii) COVID-19: Stage 1 – In this condition, passengers had one seat gap between each other i.e. all middle seats were vacant. In addition, they must follow IATA's recommended temperature check and had to follow social distancing during boarding.

iii) COVID-19: Stage 2 – In this condition, the passengers are allowed to sit next to each other. However, passengers had to follow social distancing and had to undergo temperature checks, similar to stage 1 conditions.

2.3.2 Boarding Strategies

A literature review was carried out to study different boarding strategies. **Google Scholar** and **Scopus** were used to find articles pertaining to "boarding strategy". A paper was only selected if the selected terms were found in the title, abstract or keywords. These selected papers were then searched for "boarding time" and/or "passenger experience". We discovered 57 papers, where 35 had mentions of "boarding time" and/or "passenger experience". *Seven of the most frequently* studied boarding strategies are Steffen's Method (2008), Window Middle and Aisle (WMA) , Reverse Pyramid, Random order, Back-to-Front, Half-and-Half side, and Front-to-Back. The above-mentioned experimental conditions were each tested on the seven of the most frequently studied boarding strategies.

Steffen's Method (2008) follows a strict boarding sequence. Where, window seat passengers from the most back row of the aircraft boards first, followed by a window seat passenger two rows in front of the last boarded passenger. A similar sequence is followed starting from Window seats to center seats, to aisle seats.

Window Middle and Aisle (WMA) – All passengers with the window seats board first, followed by center seats and then aisle seats. This strategy is also called Outward to inward.

Reverse Pyramid – In this strategy, passengers board from the outer back rows to the inner front of the aircraft.

Random order – There is no specific order for the passengers to board the aircraft in this strategy. There are no boarding groups.

Back-to-Front – The most traditional boarding method where, passengers start boarding the aircraft from the back rows. The aircraft is equally divided into different boarding groups. In this study, we are testing two types of back-to-front strategies: One with boarding group ranging from 1 to 4 and the other 1 to 5. Where, 1 = highest priority and 5 = lowest priority.

Half-and-Half side – This is an extension to back-to-front boarding strategy. The only difference is that the aircraft is divided into two halves (left and right). Each half is consisting of 3 boarding groups. The groups of the first half board first followed by the boarding groups in second half.

Front-to-Back – In this strategy, the passengers start boarding the aircraft from the front rows. Rows of the aircraft are equally divided into different boarding groups. These strategies are represented graphically in **Figure 2**.

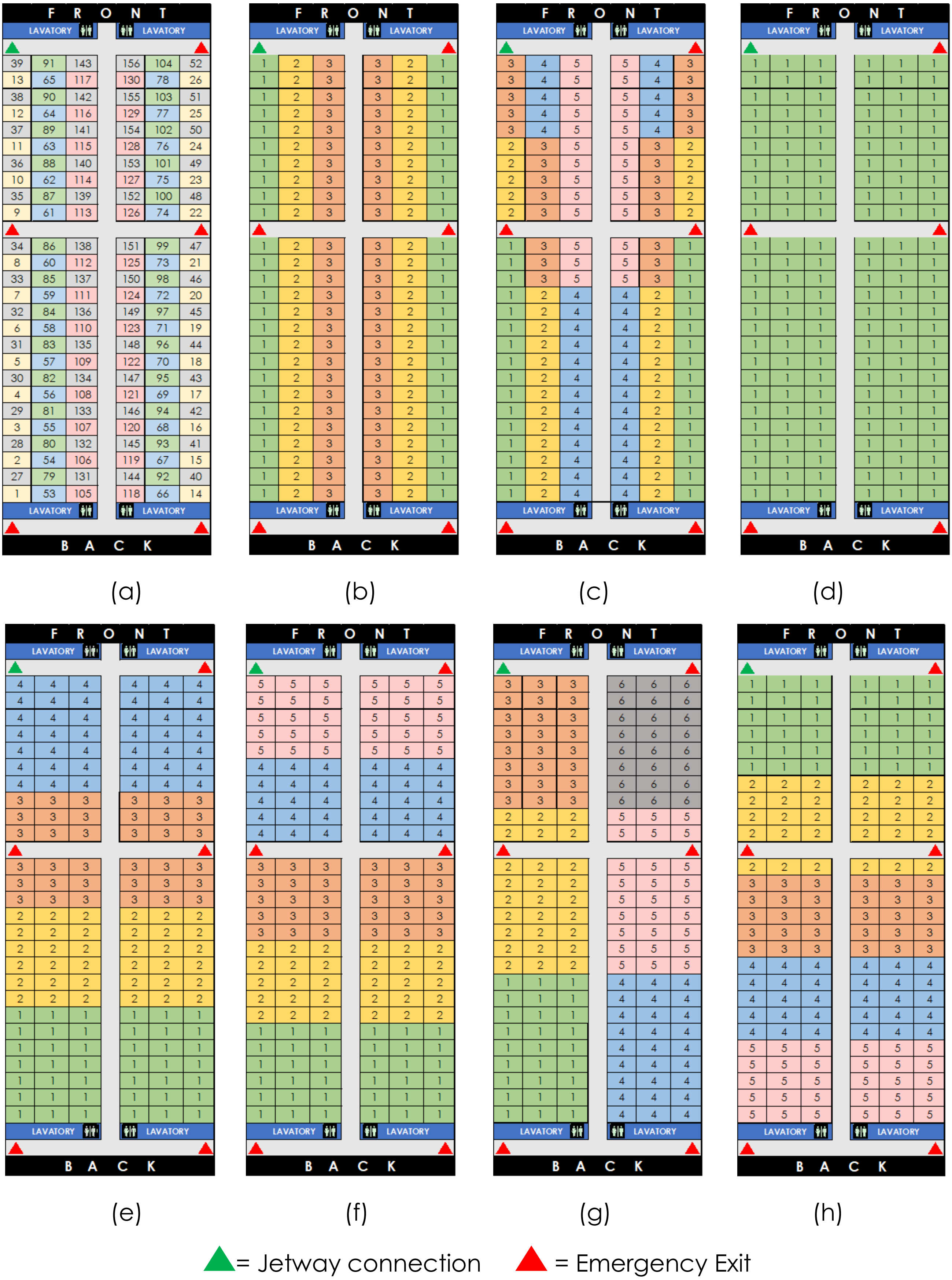

Figure 2 illustrates the different boarding strategies, for baseline (pre-COVID-19 conditions). Where, a) Steffen's Method, b) Window Middle and Aisle (WMA), c) Reverse Pyramid, d) Random order, e) Back-to-Front (with 4 boarding groups), f) Back-to-Front (with 5 boarding groups), g) Half-and-Half side, h) Front-to-Back

2.4 Modeling Experiment

The VA model was run for 365 one-way flights where each run represented a full enplane boarding. These were calculated using the method of Banks *et al.* (2005). A warm up time of 47 runs was based on the method of Hoad *et al.* (2008). To identify statistical differences ($p<0.05$), a full factorial ANOVA was used. For post hoc, Tukey's test was used. All analysis was conducted using IBM SPSS Statistics, Version 24.0.

2.5 Model Validation and Verification

This study made use of validation and verification techniques of Sargent (2013).

Repeatability and Reproducibility test – The ability of the model to produce similar results when run by different operators on different devices. The VA model was run of 4 different devices: 2 PC and 2 Apple devices. Arena (Rockwell Automation) is not supported by Apple devices; therefore, a windows emulator was used.

Degenerate testing – In this test, the VA model was run on extreme conditions to check if the model was behaving as it was intended to.

Animation and Graphics test – By using the graphics and animation of the VA model, the programmer can check to see if the model is following the correct operational logic whilst running the simulation.

Face validity – To determine if real-world outputs are being produced, the modeling outcomes are presented to the subject matter experts (n = 28) (Glasgow *et al.*, 2018; Zanda *et al.*, 2018).

Data relationship correctness – In this test, pre-determined relationships between the outputs are checked.

Extreme condition test – The VA model was run on extreme conditions to see if the model responds adequately to this change. To execute this test, the VA model was run on the extreme condition tested where all passengers had more than one carry-on baggage.

3. RESULTS

An adaptable approach to modeling the process of boarding passengers in an aircraft, successfully quantified the impact of COVID-19 policies on varying boarding strategies in terms of passenger satisfaction and passenger health risk. Detailed results are described below.

3.1 Passenger Satisfaction

Total Boarding Time – For the baseline case (pre-COVID-19), a range of 18.3 to 74.1 minutes was observed across all boarding strategies. For COVID-19 Stage 1 and Stage 2, an increased range of 22 to 24% and 59 to 81% were observed, respectively. **Figure 3** illustrates this predominantly linear increase across pre-COVID19, COVID-19 stage 1 and 2 conditions.

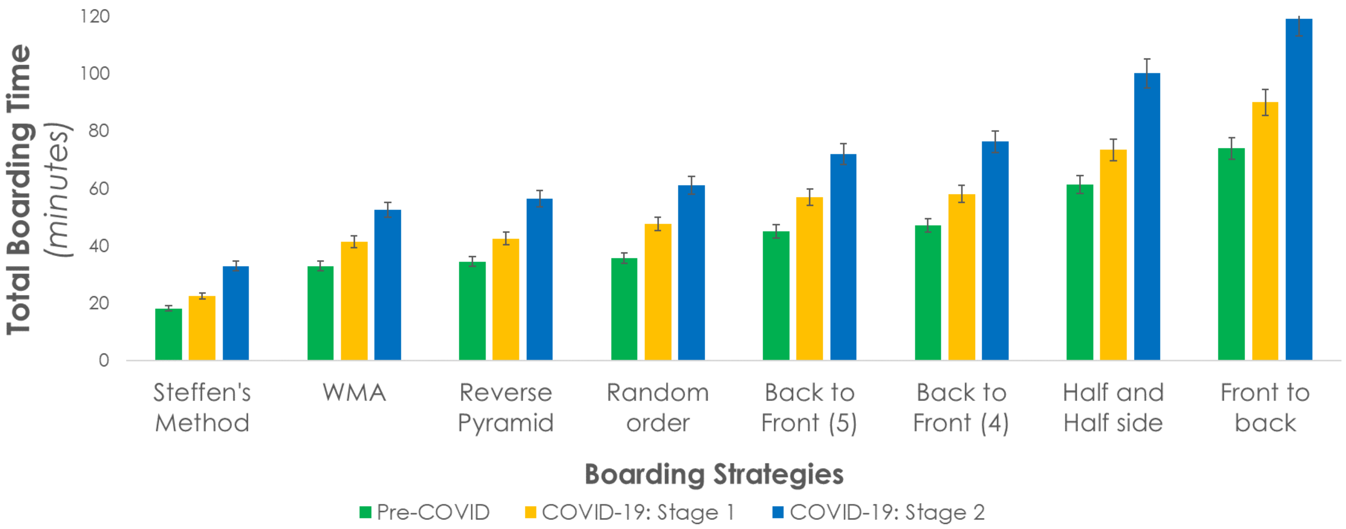

Figure 3 Illustrates the total boarding time across multiple boarding strategies, for Pre-COVID19, COVID-19: Stage 1 and Stage 2 conditions. Where, the error bars represent the standard deviation

Passenger Waiting Time (Pre-boarding) – For the baseline case (pre-COVID-19), a range of 11 to 29 minutes was observed across all boarding strategies. As illustrated in **Figure 4**, a range of -42% to 63% and an increase of 23% to 141%, were observed for COVID-19 stage 1 and stage 2 conditions, respectively.

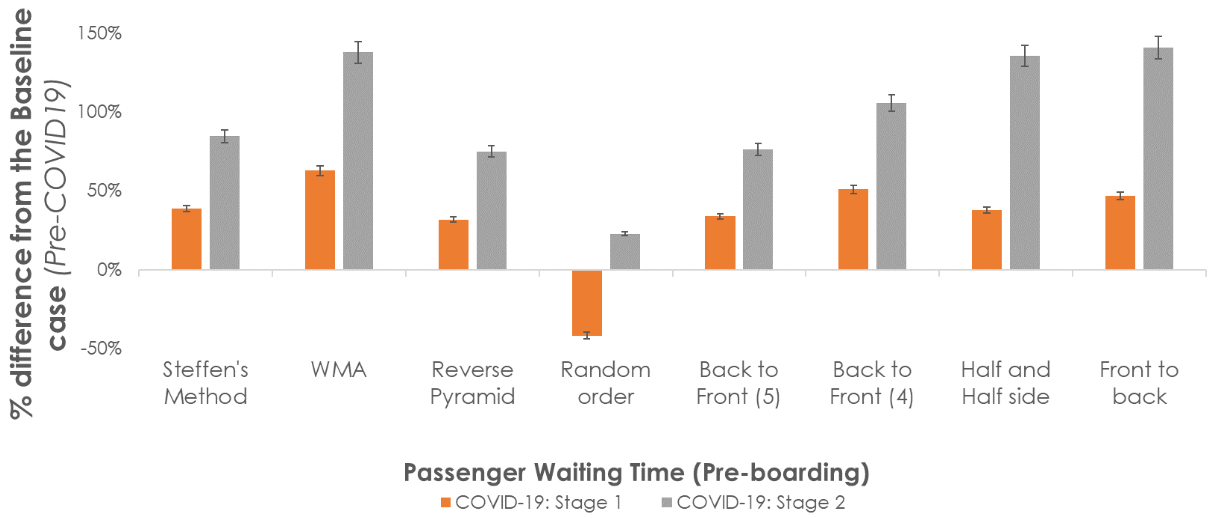

Figure 4 illustrates the percentage difference from the baseline case (Pre-COVID-19) for Passenger Waiting Time (Pre-boarding), as a function of COVID-19: Stage 1 and Stage 2. Where, the error bars represent the standard deviation

For Total Boarding Time and Passenger Waiting Time (Pre-boarding), the main effect for COVID-19 policies showed significant differences between baseline case, COVID-19 stage 1 and stage 2 ($p<0.05$). The main effect for boarding strategies, showed significant differences between Steffen's method, WMA, back-to-front (4) and front-to-back. The interaction effect for COVID-19 policies and boarding strategies was also significant ($p<0.05$). In addition, Tukey's test showed statistically significant differences for all cases of Total Boarding Time and Passenger Waiting Time (Pre-boarding). In addition, the Pearson correlation revealed a significant positive association between 'Total boarding time' and 'Passenger waiting time (pre-boarding)', $r = 0.87$, $n = 5$, $p = < 0.001$. Detailed results are illustrated in **Table 1**.

3.2 *Passenger Health Risk*

This study quantifies passenger well-being implications associated with COVID-19 travel restrictions via indicators of the Passenger Health Risk. Specific modeling results are presented below.

Jetway-Seat Time – For the baseline (Pre-COVID19) case, jetway-seat time ranged from 5.25 to 40 minutes. For COVID-19 Stage 1 and Stage 2, a decrease of -33 to -42% and an increase 4 to 83% was observed respectively. **Figure 5** illustrates these effects.

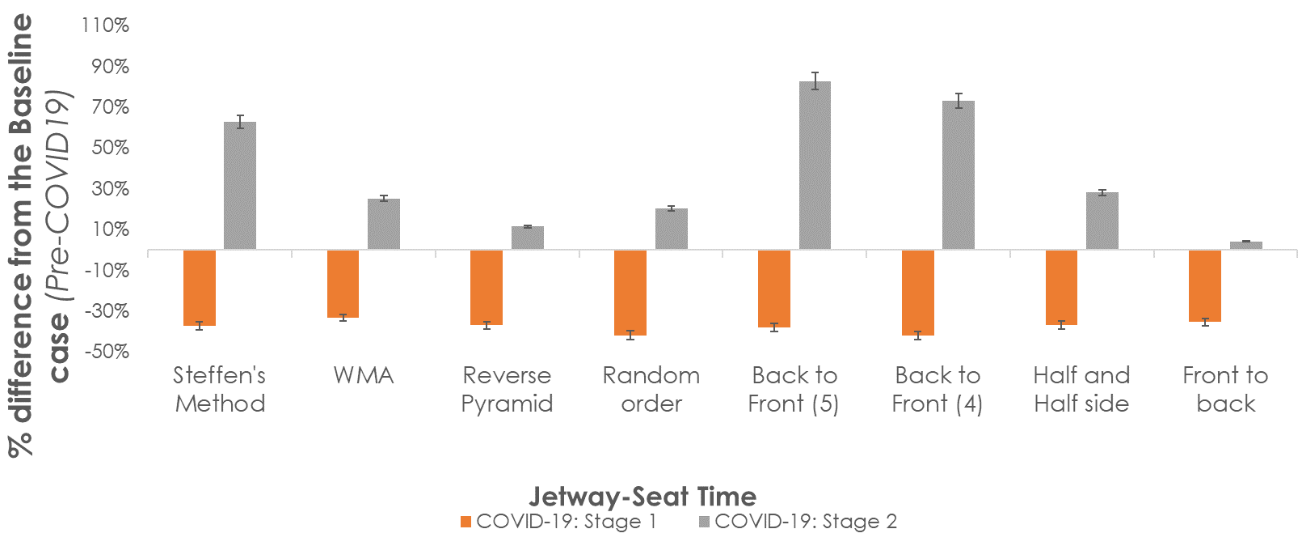

Figure 5 Illustrates the percentage difference from the baseline case (Pre-COVID-19) for jetway-seat time, as a function of COVID-19: stage 1 and stage 2. Where, the error bars represent the standard deviation

Seat Interferences – For the baseline case and COVID-19 Stage 2 condition, a consistent range of 0.5 to 84 interferences were observed. For COVID19: Stage 1, a decrease of -78 to -27% were observed. **Figure 5** illustrates the total Seat Interferences across all three conditions.

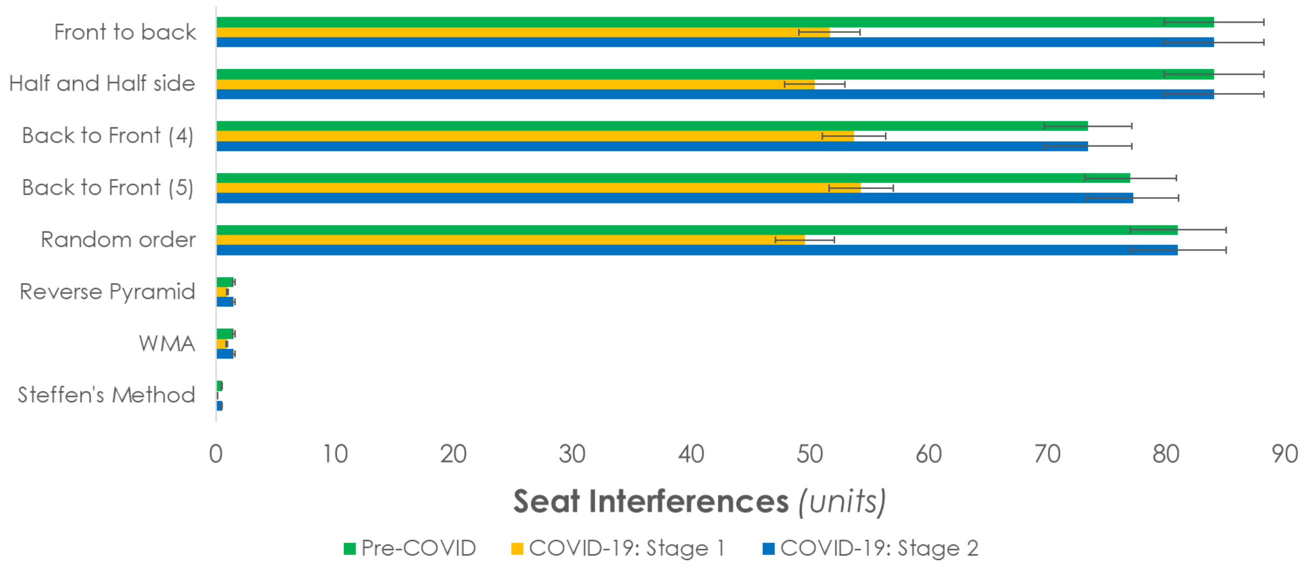

Figure 6 Illustrates the total Seat Interferences observed for all boarding strategies during Pre-COVID-19, stage 1 and stage 2 conditions. Error bars represent the standard deviation

Aisle Interferences – For the baseline case (pre-COVID-19), a range of 0.75 to 103.6 interferences were observed. For COVID19: Stage 1 and Stage 2, a range of -66% to -37% and -87% to -34% reduction of seat interferences was observed. **Figure 7** illustrates this phenomenon.

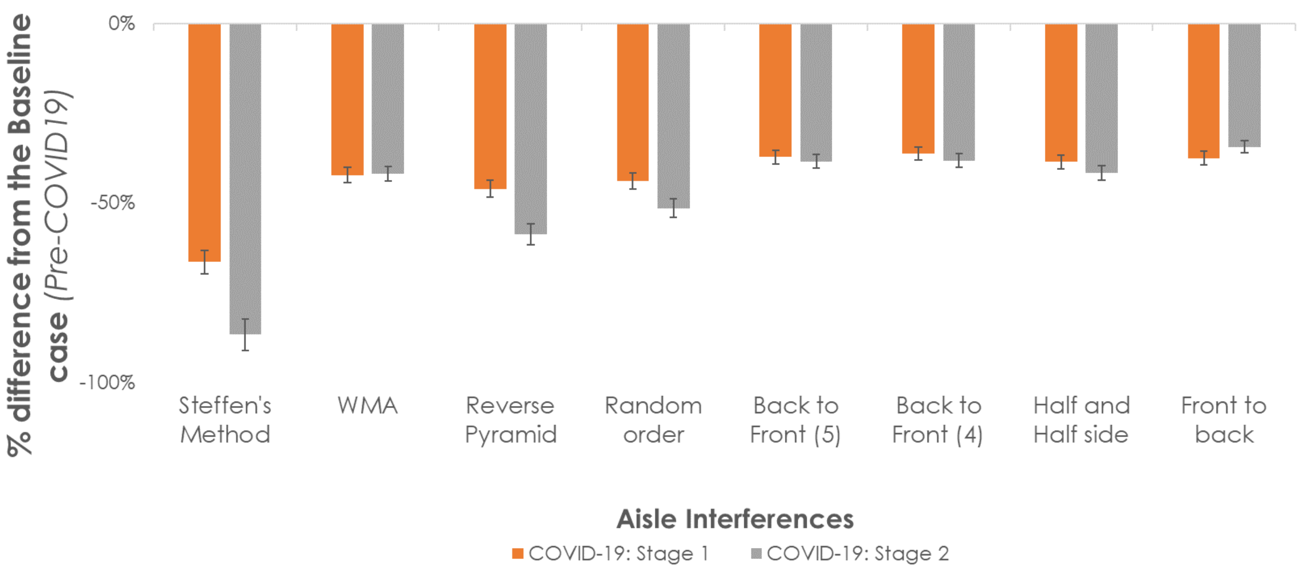

Figure 7 Shows the percentage difference from the baseline case (Pre-COVID-19) for aisle interferences, as a function of COVID-19: stage 1 and stage 2. Where, the error bars represent the standard deviation

For Jetway-Seat Time, seat interferences and aisle interferences, the main effect for COVID-19 policies showed significant differences between baseline case, COVID-19 stage 1 and stage 2 ($p<0.05$). The main effect for boarding strategies, showed significant differences between Steffen's method, WMA, back-to-front (4) and front-to-back. The interaction effect for COVID-19 policies and boarding strategies was also significant ($p<0.05$). In addition, Tukey's test showed statistically significant differences for all cases of Jetway-Seat Time, seat interferences and aisle interferences, with the exception of baseline and COVID-19 stage 2 for aisle interferences. Detailed results are illustrated in **Table 1**.

Table 1 Illustrates the detailed result of the impact of varying boarding strategy and COVID-19 conditions on passenger satisfaction and passenger health risk. Where, Pre-COVID19 condition is the baseline case

Boarding Strategy	COVID-19 Conditions	***Passenger Satisfaction Indicators***		***Passenger Health Risk Indicators***		
		Total Boarding Time	**Average Waiting Time for Passenger** *(Pre-boarding)*	**Jetway-Seat Time**	**Total Aisle Interferences**	**Total Seat Interferences**
		min, (△%)	*min, (△%)*	*min, (△%)*	*interferences, (△%)*	*interferences, (△%)*
Steffen Method (2008)	Pre-COVID19	18.3, *(0%)*	13.75, *(0%)*	5.25, *(0%)*	0.5, *(0%)*	0.75, *(0%)*
	COVID-19 Stage 1	22.66, *(23%)*	19.1, *(38%)*	3.3, *(-37%)*	0.11, *(-78%)*	0.252, *(-66%)*
	COVID-19 Stage 2	33.11, *(80%)*	25.4, *(84.7%)*	8.56, *(63%)*	0.5, *(0%)*	0.1, *(-86.6%)*
WMA	Pre-COVID19	33.1, *(0%)*	15, *(0%)*	14, *(0%)*	1.5, *(0%)*	67, *(0%)*
	COVID-19 Stage 1	41.52, *(25.4%)*	24.4, *(62.9%)*	9.35, *(-33%)*	0.9, *(-4%)*	38.7, *(-42.2%)*
	COVID-19 Stage 2	52.7, *(59%)*	35.7, *(138%)*	17.55, *(25%)*	1.5, *(0%)*	39, *(-41%)*
Reverse Pyramid	Pre-COVID19	34.6, *(0%)*	22, *(0%)*	12, *(0%)*	1.5, *(0%)*	16, *(0%)*
	COVID-19 Stage 1	42.7, *(23%)*	29, *(31.8%)*	7.58, *(-36.8%)*	0.98, *(-34.6%)*	8.64, *(-46%)*
	COVID-19 Stage 2	56.66, *(63.7%)*	38.54, *(75.1%)*	13.4, *(11.6%)*	1.5, *(0%)*	6.6, *(-58.7%)*
Random order	Pre-COVID19	35.8, *(0%)*	11, *(0%)*	25, *(0%)*	81, *(0%)*	101, *(0%)*
	COVID-19 Stage 1	47.78, *(33.4%)*	6.4, *(-41.8%)*	14.55, *(-41.8%)*	49.6, *(-38.7%)*	56.7, *(-43.8%)*
	COVID19 Stage 2	61.22, *(71%)*	13.5, *(22.7%)*	30.1, *(20.4%)*	81, *(0%)*	49, *(-51.4%)*
Back to Front (5)	Pre-COVID19	45.2, *(0%)*	29, *(0%)*	14, *(0%)*	77, *(0%)*	86, *(0%)*
	COVID-19 Stage 1	57, *(26%)*	38.84, *(33.9%)*	8.69, *(-37.9%)*	54.3, *(-29.4%)*	54, *(-37.2%)*
	COVID-19 Stage 2	72.1, *(59.5%)*	51.11, *(76%)*	25.6, *(83%)*	77.2, *(0.02%)*	53, *(-38.3%)*
Back to Front (4)	Pre-COVID19	47.14, *(0%)*	26, *(0%)*	16, *(0%)*	73.4, *(0%)*	89, *(0%)*
	COVID-19 Stage 1	58.2, *(23.4%)*	39.25, *(50.9%)*	9.3, *(-41.8%)*	53.7, *(-26.8%)*	56.7, *(-36.2%)*
	COVID-19 Stage 2	76.4, *(62%)*	53.5, *(106%)*	27.7, *(73%)*	73.4, *(0%)*	55, *(-38.2%)*
Half and Half side	Pre-COVID19	61.5, *(0%)*	35, *(0%)*	20, *(0%)*	84, *(0%)*	101, *(0%)*
	COVID-19 Stage 1	73.55, *(19.5%)*	48.2, *(37.7%)*	12.66, *(-36.7%)*	50.4, *(-40%)*	62.1, *(-38.5%)*
	COVID-19 Stage 2	100.2, *(62.9%)*	82.5, *(135%)*	25.66, *(28.3%)*	84, *(0%)*	59, *(-41.5%)*
Front to Back	Pre-COVID19	74.1, *(0%)*	40, *(0%)*	40, *(0%)*	84, *(0%)*	103.6, *(0%)*
	COVID-19 Stage 1	90.11, *(21%)*	58.7, *(46.9%)*	25.9, *(-35%)*	51.66, *(-38%)*	64.8, *(-37%)*
	COVID-19 Stage 2	119.3, *(60.9%)*	96.4, *(141%)*	41.669, *(4%)*	84, *(0%)*	68, *(-34%)*

3.3 Model Validation and Verification

Repeatability and Reproducibility test – The VA model yielded a similar range of results for all the 4 devices that the model was tested. Across all indicators, a coefficient of variation of only <6% was observed.

Degenerate testing – The VA model was run on a special condition where only 20% of the passengers were to be boarded. The total boarding time across all conditions decreased extensively.

Animation and Graphics test – Whilst running the VA model, the simulated passenger was following the programming logic of the model. Passengers were boarded in their assigned groups and temperature checks were being performed right before boarding.

Face validity – The modeling outcomes were presented to a panel of the 28 subject matter experts, and they concluded that the model was producing similar real-world outputs. Thus, validating our VA model (Zanda *et al.*, 2018).

Data relationship correctness – Whilst running the simulation model, a simultaneous decrease/increase was observed between 'total boarding time' and 'passenger waiting time'.

Extreme condition test – Stowing more than one carry-on luggage in upper baggage compartment caused delays and increased boarding time, across all boarding strategies, except for Steffen's method.

4. DISCUSSION

COVID-19 has impacted the global supply chain and operations across all industries (Forehand *et al.* 2021; Kurniawan *et al.*, 2022; Robb *et al.*, 2022). Aviation is one of the most severely impacted industries during the COVID-19 pandemic. The Airports Council International (2021) reported that the total number of yearly air travellers for the past year has been the lowest since 1997. Aviation is a driver of economic recovery and a way to reopen borders and cities (US Departments of Transportation *et al.*, 2020). IATA representing 300+ airlines globally, has implored that in an effort to revive the industry, commercial aviation processes must be updated in response to COVID-19 (Peskett, 2020). If the industry is not revived then major airliners such as Virgin Atlantic, would continue to file for bankruptcy (BBC News, 2020b; The Guardian, 2020). Some airlines have reverted to prior boarding strategies while others have introduced newer policies in response to COVID-19. Some airlines have now started to eliminate basic operating procedures just to survive this pandemic. For example, Southwest airlines, one of the biggest domestic carriers in US, is now reducing aircraft cleaning relating to COVID-19 to speed up turnround time of flights (USA Today, 2020). A decision that has received an extensive negative reaction from aviation stakeholders. Experts identify a lack of readily available proactive decision tools relating to COVID-19 in aviation, as a root-cause for this. Commercial airlines and policymakers are now forced to use 'trial and error' methodologies that in most cases increase the risk of COVID-19 transmission instead of reducing it. This paper directly addresses this research gap by providing an adaptable decision-support tool to commercial airliners and policymakers (such as ICAO, IATA etc.) to proactively test and quantify the changes due to the COVID-19 pandemic in existing passenger air-transport services, specifically aircraft boarding procedures.

4.0.1 The Need for Simulating the Aircraft Boarding Process

The passenger boarding process is not only a bottleneck but is also one of the riskiest processes for COVID-19 transmission (BBC News, 2020a; Van Den Briel *et al.*, 2003). To eliminate bottleneck, several scholars have tested different boarding strategies via computerized simulation methodologies. This study focused on the boarding process instead of in-flight COVID-19 transmission because according to the Medical Director of Infection Prevention and Control at Sunnybrook Health Sciences Centre, Toronto, Canada, "the risk of getting COVID-19 in flight is quite negligible" (The Globe and Mail, 2020), as aircrafts use hospital-grade HEPA (high-efficiency particulate air) filters that prevent transmission of infectious diseases (Government of Canada and Transport Canada, 2020; IATA, 2020a; The Globe and Mail, 2020; US Departments of Transportation *et al.*, 2020) . However, airport buildings and aircraft boarding bridges do not use these HEPA filters. Therefore, this study reports the successful development of an adaptable approach that simulates the process of enplane boarding of a commercial aircraft from the airport building through the aircraft passenger boarding bridge to the aircraft. In addition, the developed modeling capability quantifies the impact of different COVID-19 policies in terms of passenger satisfaction and passenger health risk. Thereby, answering the call by IATA (2020) that represent 300+ airlines globally, for the need of a tool to proactively test and streamline industrial operations in response to COVID-19.

Under non-pandemic circumstances, a series of elaborate experiments may be run to test different boarding strategies. Given the contagious nature of this virus, airlines and other aviation stakeholders are reluctant to experiment boarding strategies in real-life – computerized simulation models may help. As these can provide proactive insights without the risk of exposing volunteers/workers into untested and unsafe environments. Forcing passengers into unsafe and untested environment can cause a **"double hit"**. Where, the potential passenger population will decrease due to COVID-positive infections and the overall perception of air travel not being safe in pandemic scenarios will increase. Thus, further decaying the commercial aviation industry and further delaying opening of cities and borders. The developed adaptable simulation methodology measures and analyzes passenger boarding patterns under various stages of pandemic restrictions. Using this approach can not only reduce boarding time, which impacts turnaround time and cost, but this can also decrease the transmission risk of the virus. Increasing passenger and worker wellbeing, and can contribute to reviving the commercial aviation industry.

4.1 General modeling results

The developed modeling approach extends the existing approach to DES by simulating the behavioral adjustments in air-travel under various stages of pandemic restrictions. In addition, this study also models the 'different types of passengers' (adults, older-adults, child etc.) in the same simulation run; incorporates the 'interaction between passengers', passenger 'last calls' and 'failure to board the aircraft' that causes further delays as the passenger luggage must be offloaded; modeling 'newer boarding document inspection' methods and 'passenger compliance to boarding procedures and COVID-19 policies. While most studies have modeled the passenger boarding process during pre-COVID era and have incorporated some of these elements but none of the studies (to our knowledge) have included all of the above-mentioned elements in their models. Further, we present the development of an adaptable modeling approach. A discussion of modeling results is presented below.

4.1.1 Pre-COVID-19 conditions

The boarding time spanned a range of 18.3 to 74.1 minutes. Where, the lowest was for Steffen's method and highest was front-to-back strategy. The boarding time for other strategies such as WMA, reverse-pyramid, random-order, back-to-front (4) and (5) were 33.1, 34.6, 35.8, 45.2 and 47.14 minutes respectively. These were found to be in a similar range with Jaffar *et al.* (2011). Ranked order for boarding time was: 1) Steffen's method; 2) WMA; 3) Reverse Pyramid; 4) Random order; 5) Back-to-front (4 & 5); 6) Half-and-Half side, and 7) Front-to-back, consistent to those reported by Kierzkowski *et al.* (2017). Even though Steffen's method by far performed the best; However, the practical implementation may be quite difficult as arranging passengers into boarding group may be difficult and demand more work from gate agents (Steiner and Philipp, 2009). Similar to the work of Coppens *et al.* (2018) and Qiang *et al.* (2014), reverse-pyramid outperformed all boarding strategies with the exception of Steffen's method and WMA. In addition, the lowest seat and aisle interferences were for Steffen's method, WMA and reverse-pyramid, consistent with previously published work (Coppens *et al.*, 2018; Van Den Briel *et al.*, 2003). The VA model was tested on the condition where all passengers had more than one carry-on baggage; This caused delays in boarding time across all boarding strategies, except for Steffen's method – consistent with the findings of Steffen and Hotchkiss (2012). In addition, sometimes the simulant passengers had to walk backwards to find a spot to store luggage. This was found consistent with work of Marelli *et al.* (1998).

4.1.2 COVID-19 Stage 1 condition

It was expected that the boarding time would decrease because now the aircraft was operating at a ~60% capacity. On the contrary, the total boarding time increased for all boarding strategies because newer COVID-19 policies dictate that the body temperature all passengers must be taken to identify if a passenger COVID-19 positive, before they are boarding the aircraft. In addition, the passengers must now follow safe distancing protocols i.e., 2m distance apart. These contributed to increase in total boarding time. This increase ranged from 20% to 33%. Similarly, the passenger waiting time (pre-boarding) ranged from -42% to 63%. However, jetway-seat time during aircraft boarding, seat and aisle interferences, all decreased by up to -42%, -78% and -66% respectively. Thus, decreasing the overall passenger health risk– a finding consistent with the work of Barnett (2020).

4.1.3 COVID-19 Stage 2 condition

The total boarding time and passenger waiting time (pre-boarding) increased, as expected, specifically up to 81% and 141%. In addition to the safe distancing protocol and temperature checks, the aircraft is now operating again at full passenger capacity. Therefore, seat interferences were similar to the pre-COVID-19 conditions. However, aisle conditions saw a decrease of up to -87% as the passengers were now observing safe distancing and walking slower, out of fear of contracting COVID-19. Instances where there could have been an aisle interference did not occur as in some cases the simulant-passenger had already stored their carry-on bag in the overhead compartment before the other simulant-passenger came in close contact. The exposure time also increased up to 60% as passengers are walking slower and following safe distancing, unlike COVID-19 Stage 1 condition.

Pearson correlation revealed a significant positive association between 'Total boarding time' and 'Passenger waiting time (pre-boarding)', $r = 0.87$, $n = 5$, $p = < 0.001$. Therefore, newer policies designed to improve the boarding time, must reduce passenger waiting time (pre-boarding).

The forementioned COVID-19 stage 1 and stage 2 protocols might be specific to some countries only. However, the developed modeling approach is adaptable and can therefore the VA model can be adapted (by changing modeling inputs and experimental conditions) to match the context under study. The aim of this study was not to give a definitive answer rather than developing an adaptable approach that can be used to test other conditions.

4.2 Impact of COVID-19 Virus Transmission on Boarding Strategies

4.2.1 Boarding Strategies Tested

The aim of this paper was not to test all existing boarding strategies, rather than provide an adaptable modeling approach that allows aviation stakeholders, infection control personnel and other decision makers a platform the test and create new boarding strategies. As a demonstrator case, seven of the most frequently studied boarding strategies were tested. A boarding strategy was selected through a literature review exploring *Google Scholar* and *Scopus*, to find articles pertaining to "boarding strategy". A paper was only selected if the selected terms were found in the title, abstract or keywords. These selected papers were then searched for "boarding time" and/or "passenger experience". 54 papers were discovered, where 35 had mentions of "boarding time" and/or "passenger experience". *Seven of the most frequently* studied boarding strategies are Steffen's Method (2008), Window Middle and Aisle (WMA) , Reverse Pyramid, Random order, Back-to-Front, Half-and-Half side, and Front-to-Back.

4.2.2 Indicators for Passenger Health Risk and Passenger Satisfaction

In this study, jetway-seat time, seat and aisle interferences were considered as indicators of passenger health risk. These metrics are of concern to the passenger's health and reflects potential exposure to the COVID-19 virus through air and surfaces (e.g. touching the other passenger's armrest and headrest when vacating the seat, to allow the other passenger to sit down in the Window/Middle seat etc.). The COVID-19 virus may spread through air droplets and surfaces as they maybe later touched by the passengers who may touch their noses and mouths Pre-boarding passenger waiting time was not considered as an indicator because according to experts, passengers may have more space to maintain safe distancing at the airport. But, boarding narrow-body jetways and single aisle aircrafts create high-density clusters during boarding that contribute to high-risk for COVID-19 transmission (BBC News, 2020a). Due to these high-density clusters, seat and aisle interferences also increase that directly impact Jetway-Seat Time. Total boarding time and pre-boarding passenger waiting time were used as indicators of passenger satisfaction, as previous peer-reviewed published work (Jaehn and Neumann, 2015; Wittmann, 2019), have considered these similar variables as indicators for passenger satisfaction.

4.2.3 Passenger Health Risk vs. Boarding Strategies

In terms of COVID-19 virus transmission, Steffen's method and reverse pyramid were again the best, followed by WMA. Other strategies such as Back-and-front, random order, half-and-half side, and front-to-back were found to be extremely high risk.

In Steffen's method, sorting passenger's out by their unique individual boarding group prior to moving passengers in the jetway and aircraft, led to no seat and aisle interferences. This extensively contributed to decreased Jetway-Seat Time inside the aircraft of 3.3 min to 8.5min for both stage 1 and stage 2 COVID-19 policies. However, boarding time increased by up to 64%. Reverse pyramid was found to be a slightly less effective than Steffen's method in terms of minimizing risk of COVID-19 but it was much easier to implement as it did not require extensive work to be done by the check-in crew. For both COVID-19 stages, only up to 1.5 and 6.6 seat and aisle interferences along with a Jetway-Seat Time of 13 minutes. and boarding time increased by only 33% and 64%, respectively. Reverse pyramid's success can be attributed to filling the aircraft outside-in from back of the aircraft to front, which is a combination of two approaches WMA and back-to-front. While the standalone WMA method, which fills the aircraft from outside-in, is easier to implement but a Jetway-Seat Time of up to 18 minutes along with 39 aisle interferences make it a less attractive candidate despite ~2 seat interferences and a 59% increase in boarding time. The standalone Back-and-front (4 & 5, both) method saw extensive seat and aisle interferences, specifically, 87 and 101 interferences respectively, and an increase in average Jetway-Seat Time up to 25.6 and 27.7minutes that contributed to a 62% increase in boarding time.

For the Random-order boarding strategy, the average Jetway-Seat Time increased up to 30minutes for both COVID-19 stages, However, a decrease of -42% of pre-boarding passenger waiting time was observed for random-order boarding strategy because there were no assigned boarding groups. All passengers started the boarding process (moving to the jetway to aircraft) faster and this led to increased seat and aisle interferences of up to 81 and 57 interferences, creating several high-density clusters that led to up to 71% increase in boarding time. Thereby, proving to be the worst boarding strategy to minimize COVID-19 transmission (passenger health risk) and decreased passenger satisfaction. Similarly, half-and-half side, and front-to-back, all have increased risk for passenger health risk. As these not only have up to 68 and 84 aisle and seat interferences, but an exposure time ranged from 25 to 41 minutes was observed along with an up to 63% increase in boarding time.

Therefore, it is recommended (based on preliminary results), Stephen's Method, Reverse Pyramid and WMA are the most effective in terms of passenger satisfaction and passenger health risk. However, field validation studies are further required to affirm this. In Stephen's method, all passengers essentially have their own boarding group. This maybe difficult to implement. Airlines and airport authorities may use Reverse Pyramid, followed by WMA, as they are much easier to implement and have minimal differences in terms of passenger satisfaction and passenger health risk in comparison to Stephen's method.

4.3 Methodological Modeling Issues and Future Work

The VA model spans a wide range of operational conditions. These may need to be updated for newer conditions. With the exception of COVID-19 stage 1 condition, the VA model was run under the modeling condition where all seats were filled. Where, two boarding agents performed all boarding operations. Such may not be the case in real-life as the number of boarding agents vary from flight to flight. The aim of this study was not to give a definitive answer rather than developing an adaptable approach that can be used to test other conditions. This demonstrator (VA) model tested the impact of changes in COVID-19 policies on a smaller aircraft similar to an Airbus A320 or Boeing 737, with only economy seats. This adaptable modeling approach can be adapted to test bigger aircrafts such as Boeing 777 or Airbus A380 as well, along with divisions of Business and Premium Economy classes, and Priority Boarding Groups. In addition, all boarding strategies tested made use of jetway instead of tarmac boarding via ground transport (via bus). Further, the walking speed of an 'average' passenger was used. In practice, these may vary by passenger, as some passengers maybe more agile than others. The Centers for Disease Control and Prevention (CDC), ICAO, IATA, regional airport authorities and others, have been updating COVID-19 guidelines very frequently. Therefore, major changes in the boarding guidelines have been considered in this study. Given the adaptable nature of this modeling approach, newer policies can easily be added by adapting the modeling inputs to specific contexts (Section 2.1). Other limitations include: the modeling logic was developed using SME with international experience based out of Canada. The operational logic can be adapted to the context of specific regions and countries via focus groups.

Future work includes extending the VA model to reflect aircraft turnaround operations and testing boarding strategies on aircrafts with different seating classes i.e. 5% business, 10% premium economy and 85% economy class, along with priority boarding. In addition, testing boarding strategies that make use of tarmac boarding (via ground transport), enhancing the programming logic with SMEs globally, and extending the VA model to include more indicators of passenger satisfaction and passenger health risk. The VA model has face validity; While the internal validation checks deem the modeling approach to be successful, a live field study is required to validate this modeling approach. Further testing is required.

4.4 Implications to the Aviation industry

The developed modeling capability addresses the recommended need by Boston Consulting Group (2020), that commercial airliners should also prepare for ramping up operations once countries start to reopen. This study provides a methodological framework for quantifying the impact of COVID-19 pandemic on the air-transport system. The ability to model the process of boarding passengers in the aircraft provides a springboard to test develop and test newer boarding strategies that can take in to account future pandemics. This VA modeling capability is useful for **airlines** and **airport managers**, for their operational planning strategies; **architects**, to test and design new aircraft layouts and seating arrangements; **quality improvement leaders**, to create safer work environments for commercial aviation workers, **healthcare practitioners**, to plan for reported outbreaks in the aircraft and **policy makers**, to develop and proactively test the impact of newer policies. This approach can now be extended to test potential operational strategies and technical design changes that are of interest to the stakeholders. The developed modeling capability acts as a response to IATA (2020a) and International Civil Aviation Organization [ICAO], (2020), need for a tool that can proactively test newly adapted policies for COVID-19. Furthermore, this research acts as a direct response to US Department of Transportation, Homeland Security *et al.*, (2020) need to reduce decreasing the waiting time for the traveling passengers.

The modeling approach developed here offers a cost-effective and, above all, a safe alternative to the current trial-and-error methods. While preliminary results are promising and compare favorably to subject matter experts; however, further testing is required to extend and validate this model by means of a field study test.

5. CONCLUSION

A novel approach to DES modeling of the passenger boarding process has been successfully developed. This adaptable modeling approach tested and quantified the impact of COVID-19 on the passenger boarding process in terms of efficiency, and the risk of virus transmission. This study reports a trade-off: the risk of COVID-19 transmission decreases by up to -87% whilst passenger satisfaction deteriorates, specifically, total boarding time and passenger waiting time (pre-boarding) by up to 81% and 114% respectively. Steffen's method, reverse pyramid and WMA were the most effective to minimize COVID-19 risk in both stage 1 and stage 2 policies. Steffen's method maybe harder to implement yet it is most effective under COVID-19 conditions. However, reverse pyramid and WMA can be considered most effective with a minor trade-off i.e. slightly increased total boarding time and minor increase in aisle interferences, with increase ease in implementation. COVID-19 Stage 1 policies were found to be much effective in terms of minimizing passenger health risk with minor increase in boarding, in comparison to COVID-19 stage 2 policies time. These models are potential decision-support engines to test and streamline the boarding process that enhance passenger and worker safety. While further testing and development of this modeling capability is required, the developed modeling approach provides a tool for stakeholders to guide planning and policy development in regard to the COVID-19 pandemic and its recovery phases.

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REFERENCES

Airports Council International. (2021). The impact of COVID-19 on the airport business and the path to recovery. Retrieved from https://aci.aero/2021/11/01/the-impact-of-covid-19-on-the-airport-business-and-the-path-to-recovery-3/

Ball, M., Barnhart, C., Dresner, M., Hansen, M., Neels, K., Odoni, A., … Voltes, A. (2010). Total Delay Impact Study. *Nextor*, 5–14, 25–30. Retrieved from http://www.isr.umd.edu/NEXTOR/pubs/TDI_Report_Final_10_18_10_V3.pdf

Banks, J., Carson, J. S. I., Nelson, N. L., and Nicol, D. M. (2005). *Discrete-Event System Simulation* (4th ed.). Prentice Hall International Series in Industrial and Systems Engineering.

Barnett, A. (2020). Covid-19 Risk Among Airline Passengers: Should the Middle Seat Stay Empty? *MedRxiv*. https://doi.org/10.1101/2020.07.02.20143826

Bazant, M. Z., and Bush, J. W. M. (2021). A guideline to limit indoor airborne transmission of COVID-19. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(17). https://doi.org/10.1073/pnas.2018995118

Bazargan, M. (2007). A linear programming approach for aircraft boarding strategy. *European Journal of Operational Research*, *183*(1), 394–411. https://doi.org/10.1016/j.ejor.2006.09.071

BBC News. (2020a). How Covid-19 could change plane boarding. Retrieved from https://www.bbc.com/worklife/article/20200612-why-coronavirus-will-change-how-we-board-a-plane

BBC News. (2020b). Virgin Atlantic warns it is running out of money. Retrieved from https://www.bbc.com/news/business-53659844?fbclid=IwAR1EJ_VK2RZSQIhzlBOhLx3UgPKEWZ0zJYwuhm_TQPZ3coYTuYhvl2XALUE

Boston Consulting Group. (2020). *The Post-COVID-19 Flight*

Plan for Airlines. (D.-M. Molenaar, F. Bosch, J. Guggenheim, P. Jhunjhunwala, H. H. Loh, and B. Wade, Eds.). Retrieved from https://image-src.bcg.com/Images/BCG-The-Post-COVID-19-Flight-Plan-for-Airlines-Mar-2020_tcm9-242718.pdf

Chakraborty, S. (2020). Healthcare quality and hospital financial performance: A multilevel framework. *Operations and Supply Chain Management*, *13*(3), 233–243. https://doi.org/10.31387/OSCM0420265

Ching-Chung, K. (2015). An Improved Zero-One Linear Programming Model for the Plane Boarding Problem. In *Applications of Management Science* (Vol. 17, pp. 53–69). Emerald Group Publishing Limited. https://doi.org/10.1108/S0276-897620140000017003

CNN. (2020a). Airlines and TSA report 96% drop in air travel as pandemic continues. Retrieved from https://www.cnn.com/2020/04/09/politics/airline-passengers-decline/index.html

CNN. (2020b). Virgin Atlantic files for bankruptcy in the US to secure its rescue deal. Retrieved from https://www.cnn.com/2020/08/04/business/virgin-atlantic-bankruptcy/index.html

Coppens, J., Dangal, S., Vendel, M., Anjani, S., Akkerman, S., Mastrigt, S. H. van, and Vink, P. (2018). Improving airplane boarding time: A review, a field study and an experiment with a new way of hand luggage stowing. *International Journal of Aviation, Aeronautics, and Aerospace*, *5*(2). https://doi.org/10.15394/ijaaa.2018.1200

Cotfas, L. A., Delcea, C., Milne, R. J., and Salari, M. (2020). Evaluating classical airplane boarding methods considering COVID-19 flying restrictions. *Symmetry*, *12*(7), 1–26. https://doi.org/10.3390/SYM12071087

Delcea, C., Cotfas, L. A., Chiriţă, N., and Nica, I. (2018). A two-door airplane boarding approach when using apron buses. *Sustainability (Switzerland)*, *10*(10). https://doi.org/10.3390/su10103619

Fatemi, M., Millan, J., Stevenson, J., Yu, T., and O'Young, S. (2008). Discrete event control of an unmanned aircraft. *2008 9th International Workshop on Discrete Event Systems*, (July 2015). https://doi.org/10.1109/WODES.2008.4605971

Ferrari, P., and Nagel, K. (2005). Robustness of efficient passenger boarding strategies for airplanes. *Transportation Research Record*, (1915), 44–54. https://doi.org/10.3141/1915-06

Forbes. (2021). Will Sir Richard Branson Take Virgin Atlantic From Bankruptcy To IPO ?, (L). Retrieved from https://www.forbes.com/sites/michaelgoldstein/2021/08/10/will-sir-richard-branson-take-virgin-atlantic-from-bankruptcy-to-ipo/?sh=135bf4d544ea

Forehand, K., Román, J., and Schaefer, T. (2021). Supply chain efficiency in the discount store industry post covid-19: Applying the supply chain efficiency ratio. *Operations and Supply Chain Management*, *14*(4), 423–430. https://doi.org/10.31387/oscm0470313

Fuchte, J. C. (2014). Enhancement of aircraft cabin design guidelines with special consideration of aircraft turnaround and short range operations. *Ph.D. Thesis, Technische Universität Hamburg-Harburg, Hamburg, Germany, 2014*, 1–141.

Glasgow, S. M., Perkins, Z. B., Tai, N. R. M., Brohi, K., and Vasilakis, C. (2018). Development of a discrete event simulation model for evaluating strategies of red blood cell provision following mass casualty events. *European Journal of Operational Research*, *270*(1), 362–374. https://doi.org/10.1016/j.ejor.2018.03.008

Government of Canada, and Transport Canada. (2020). *COVID-19: Guidance Material for Air Operators Managing Travellers to Canada at International Airports*. Retrieved from https://tc.canada.ca/en/initiatives/covid-19-measures-updates-guidance-tc/guidance-material-air-operators

Gulf News. (2020). Emirates airline to cut up to 9,000 jobs.

Günal, M. M., and Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation*, *4*(1), 42–51. https://doi.org/10.1057/jos.2009.25

Hoad, K., Robinson, S., and Davies, R. (2008). Automating warm-up length estimation. *Proceedings - Winter Simulation Conference*, 532–540. https://doi.org/10.1109/WSC.2008.4736110

IATA. (2020a). Restarting aviation following COVID-19 Medical evidence for various strategies being discussed as at 8 May 2020 IATA Medical Advisory Group. *Medical Advisory Group*, (May). Retrieved from https://www.iata.org/contentassets/f1163430bba94512a583eb6d6b24aa56/covid-medical-evidence-for-strategies-200508.pdf

IATA. (2020b). "The worst may be yet to come" – Impacts of COVID-19 on European Aviation and Economy Increasing. Retrieved from https://www.iata.org/en/pressroom/pr/2020-06-18-01/?fbclid=IwAR0oZ3kFsHjibDKjVamK4W1VIKcMluUbUMe70fUYynEumvx_rulfrIfRHSM

International Civil Aviation Organization (ICAO). (2020). Effects of Novel Coronavirus (COVID-19) on Civil Aviation: Economic Impact Analysis Air Transport Bureau Contents, (June). Retrieved from https://www.icao.int/sustainability/Documents/COVID-19/ICAO_Coronavirus_Econ_Impact.pdf

Iwata, C., and Mavris, D. (2013). Object-oriented discrete event simulation modeling environment for aerospace vehicle maintenance and logistics process. *Procedia Computer Science*, *16*, 187–196. https://doi.org/10.1016/j.procs.2013.01.020

Jaehn, F., and Neumann, S. (2015). Airplane boarding. *European Journal of Operational Research*, *244*(2), 339–359. https://doi.org/10.1016/j.ejor.2014.12.008

Jafer, S., and Mi, W. (2017). Comparative study of aircraft boarding strategies using cellular discrete event simulation. *Aerospace*, *4*(4). https://doi.org/10.3390/aerospace4040057

Jaffar, N., Abdul-Tharim, A. H., Mohd-Kamar, I. F., and Lop, N. S. (2011). A literature review of ergonomics risk factors in construction industry. *Procedia Engineering*, *20*, 89–97. https://doi.org/10.1016/j.proeng.2011.11.142

Jun, J. B., Jacobson, S. H., and Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, *50*(2), 109–123. https://doi.org/10.1057/palgrave.jors.2600669

Khatib, A. N., Carvalho, A. M., Primavesi, R., To, K., and Poirier, V. (2021). Navigating the risks of flying during COVID-19: A review for safe air travel. *Journal of Travel Medicine*, *27*(8), 1–9. https://doi.org/10.1093/JTM/TAAA212

Kierzkowski, A., and Kisiel, T. (2017). The Human Factor in the Passenger Boarding Process at the Airport. *Procedia Engineering*, *187*, 348–355. https://doi.org/10.1016/j.proeng.2017.04.385

Kierzkowski, A., and Kisiel, T. (2020). Simulation model of security control lane operation in the state of the COVID-19 epidemic. *Journal of Air Transport Management*, *88*(June), 101868. https://doi.org/10.1016/j.jairtraman.2020.101868

Kurniawan, F., Musa, S. N., Moin, N. H., and Sahroni, T. R. (2022). A Systematic Review on Factors Influencing Container Terminal's Performance. *Operations and Supply Chain Management*, *15*(2), 174–192. https://doi.org/10.31387/oscm0490339

Lee, C., Jung, E., Kang, S., Petrick, J. F., and Park, Y. (2022). Impact of perception of COVID-19 on NPI, job satisfaction, and customer orientation: Highlighting three types of NPIs for the airline industry. *Journal of Air Transport Management*, *100*(February).

Legato, P., and Mazza, R. M. (2001). Berth planning and resources optimisation at a container terminal via discrete event simulation. *European Journal of Operational Research*, *133*(3), 537–547. https://doi.org/10.1016/S0377-2217(00)00200-9

Lusiantoro, L., Mara, S. T. W., and Rifai, A. P. (2022). A Locational Analysis Model of the COVID-19 Vaccine Distribution. *Operations and Supply Chain Management*, *15*(2), 240–250. https://doi.org/10.31387/oscm0490344

Malandri, C., Mantecchini, L., and Reis, V. (2019). Aircraft turnaround and industrial actions: How ground handlers' strikes affect airport airside operational efficiency. *Journal of Air Transport Management*, *78*, 23–32. https://doi.org/https://doi.org/10.1016/j.jairtraman.2019.04.007

Marelli, S., Mattocks, G., and Merry, R. (1998). The role of computer simulation in reducing airplane turn time. *Boeing Aero Magazine*, *1*.

Meng, Y., Khan, A., Bibi, S., Wu, H., Lee, Y., and Chen, W. (2021). The Effects of COVID-19 Risk Perception on Travel Intention: Evidence From Chinese Travelers. *Frontiers in Psychology*, *12*(July), 1–16. https://doi.org/10.3389/fpsyg.2021.655860

Milne, R. J., Cotfas, L. A., Delcea, C., Salari, M., Craciun, L., and Molanescu, A. G. (2020). Airplane boarding method for passenger groups when using apron buses. *IEEE Access*, *8*, 18019–18035. https://doi.org/10.1109/ACCESS.2020.2968410

Milne, R. J., and Kelly, A. R. (2014). A new method for boarding passengers onto an airplane. *Journal of Air Transport Management*, *34*, 93–100. https://doi.org/10.1016/j.jairtraman.2013.08.006

Milne, R. J., Salari, M., and Kattan, L. (2018). Robust optimization of airplane passenger seating assignments. *Aerospace*, *5*(3). https://doi.org/10.3390/aerospace5030080

Perez, J., de Looze, M. P., Bosch, T., and Neumann, W. P. (2014). Discrete event simulation as an ergonomic tool to predict workload exposures during systems design. *International Journal of Industrial Ergonomics*, *44*(2), 298–306. https://doi.org/10.1016/j.ergon.2013.04.007

Peskett, J. (2020). How To Reboot The Airline Industry Post-Covid-19. Retrieved from https://www.aviationbusinessme.com/covid-19/21373-how-to-reboot-the-airline-industry-post-covid-19

Qiang, S. J., Jia, B., Xie, D. F., and Gao, Z. Y. (2014). Reducing airplane boarding time by accounting for passengers' individual properties: A simulation based on cellular automaton. *Journal of Air Transport Management*, *40*, 42–47. https://doi.org/10.1016/j.jairtraman.2014.05.007

Qureshi, S. M., Purdy, N., and Neumann, W. P. (2020). Development of a Methodology for Healthcare System Simulations to Quantify Nurse Workload and Quality of Care. *IISE Transactions on Occupational Ergonomics and Human Factors*, *8*(1), 27–41. https://doi.org/10.1080/24725838.2020.1736692

Qureshi, S. M., Purdy, N., and Neumann, W. P. (2021). A Computerized Model Quantifying the Impact of Geographical Patient- Bed Assignment on Nurse Workload and Quality Care. *Nursing Economic$*, *39*(1), 23–35.

Rajendran, S., and Shulman, J. (2020). Study of emerging air taxi network operation using discrete-event systems simulation approach. *Journal of Air Transport Management*, *87*(May). https://doi.org/10.1016/j.jairtraman.2020.101857

Robb, C. A., Kang, M., and Stephens, A. R. (2022). The effects of dynamism, relational capital, and ambidextrous innovation on the supply chain resilience of U.S. firms amid COVID-19. *Operations and Supply Chain Management*, *15*(1), 1–16. https://doi.org/10.31387/oscm0480326

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation*, *7*(1), 12–24. https://doi.org/10.1057/jos.2012.20

Schmidt, M., Heinemann, P., and Hornung, M. (2017). Boarding and Turnaround Process Assessment of Single- and Twin-Aisle Aircraft. In *55th AIAA Aerospace Sciences Meeting*. https://doi.org/10.2514/6.2017-1856

Schultz, M. (2017). The Seat Interference Potential as an Indicator for the Aircraft Boarding Progress. In *SAE Technical Paper*. SAE International. https://doi.org/10.4271/2017-01-2113

Schultz, M., and Schmidt, M. (2018). Advancements in passenger processes at airports from aircraft perspective. *Sustainability (Switzerland)*, *10*(11). https://doi.org/10.3390/su10113877

Seglins, D., Guerriero, L., and Clementson, L. (2020). Canadian flight crews demand protective suits as more than a dozen fall ill with COVID-19. Retrieved from https://www.cbc.ca/news/health/flight-attendants-protective-suits-1.5513439

Steffen, J. H. (2008). Optimal boarding method for airline passengers. *Journal of Air Transport Management*, *14*(3), 146–150. https://doi.org/10.1016/j.jairtraman.2008.03.003

Steffen, J. H., and Hotchkiss, J. (2012). Experimental test of airplane boarding methods. *Journal of Air Transport Management*, *18*(1), 64–67. https://doi.org/10.1016/j.jairtraman.2011.10.003

Steiner, A., and Philipp, M. (2009). Speeding up the airplane boarding process by using pre-boarding areas boarding areas. *9th Swiss Transport Research Conference*, (September 2009).

Suau-Sanchez, P., Voltes-Dorta, A., and Cugueró-Escofet, N. (2020). An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it? *Journal of Transport Geography*, *86*(June), 102749. https://doi.org/10.1016/j.jtrangeo.2020.102749

Sun, X., Wandelt, S., Zheng, C., and Zhang, A. (2021). COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. *Journal of Air Transport Management*, *94*, 102062. https://doi.org/10.1016/j.jairtraman.2021.102062

Tang, J. W., Marr, L. C., Li, Y., and Dancer, S. J. (2021). Covid-19 has redefined airborne transmission. *The BMJ*, *373*(April), 1–2. https://doi.org/10.1136/bmj.n913

Tang, T., Wu, Y.-H., Huang, H., and Caccetta, L. (2012). An aircraft boarding model accounting for passengers' individual properties. *Transportation Research Part C: Emrging Technologies*, *22*, 1–16.

The Globe and Mail. (2020, July 26). How safe is flying during COVID-19 ? Retrieved from https://www.theglobeandmail.com/life/health-and-fitness/article-what-are-my-chances-of-catching-covid-19-if-i-take-a-flight/

The Guardian. (2020). Virgin Atlantic files for bankruptcy protection as Covid continues to hurt airlines. Retrieved from https://www.theguardian.com/business/2020/aug/04/virgin-atlantic-files-for-bankruptcy-as-covid-continues-to-hurt-airlines

Truong, N. T., Dang-Pham, D., McClelland, R., and Nkhoma, M. (2020). Exploring the impact of innovativeness of hospitality service operation on customer satisfaction. *Operations and Supply Chain Management*, *13*(3), 307–319. https://doi.org/10.31387/OSCM0420272

US Departments of Transportation, Homeland Security, and Health and Human Services. (2020). Runway to Recovery: The United States Framework for Airlines and Airports to Mitigate the Public Health Risks of Coronavirus, (July). Retrieved from https://search.bvsalud.org/global-literature-on-novel-coronavirus-2019-ncov/resource/en/grc-740792

USA Today. (2020, August 3). Southwest reduces aircraft cleaning between flights , focusing on tray tables over seat belts. Retrieved from https://www.usatoday.com/story/travel/2020/08/03/southwest-airlines-reduces-cleaning-between-flights-turnaround-timesaving/5578918002/

Uvet, H. (2020). Importance of logistics service quality in customer satisfaction: An empirical study. *Operations and Supply Chain Management*, *13*(1), 1–10. https://doi.org/10.31387/OSCM0400248

Van Den Briel, M. H. L., Villalobos, J. R., and Hogg, G. L. (2003). The Aircraft Boarding Problem. *Proceedings of the 12th Industrial Engineering Reseach Conference(CD-ROM)*, (January 2003).

Van Landeghem, H., and Beuselinck, A. (2002). Reducing passenger boarding time in airplanes: A simulation based approach. *European Journal of Operational Research*, *142*(2), 294–308. https://doi.org/10.1016/S0377-2217(01)00294-6

Wittmann, J. (2019). Customer-oriented optimization of the airplane boarding process. *Journal of Air Transport Management*, *76*(January), 31–39. https://doi.org/10.1016/j.jairtraman.2019.02.002

World Health Organization. (2020). WHO Director-General's opening remarks at the media briefing on COVID-19-11 March 2020. Geneva, Switzerland.

Zanda, S., Zuddas, P., and Seatzu, C. (2018). Long term nurse scheduling via a decision support system based on linear integer programming: A case study at the University Hospital in Cagliari. *Computers and Industrial Engineering*, *126*(September 2017), 337–347. https://doi.org/10.1016/j.cie.2018.09.027

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