Can COVID-19 decrease pilots' operational skills? Investigating the impacts of the pandemic on pilots' proficiency using Flight Data Monitoring

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1. INTRODUCTION

Let's go back in time to five years ago. It is 2018, the international air transport just had its safest year for commercial passenger air travel with zero accidents in 2017 and IATA predicted a constant grow in air traffic with at least 4 billion air travellers in 2021 and up to 8.2 billion travellers in 2037 (IATA, 2018; Shepardson, 2018). Then, this all collapsed in 2020. Suddenly, within a few months, first in Asia, then in Europe, America, and Africa. Borders closed, passenger demand dropped by around 75%, and airports emptied of passengers and crews, turned into aircraft resuscitation rooms where only certain maintenance and security professionals moved around so as not to let their patients wither away while their airlines were in survival mode. Safety professionals were impacted too: less flights means less safety data: Flight Data Monitoring (FDM) also known as Flight Operations Quality Assurance (FOQA) programmes (i.e., the process of recording flight parameters and then analyse them to monitor safety performance) got disrupted. Even still operated flights were now in a completely different environment: new crew schedules, less traffic, and for crews, less opportunities to fly. Quite rapidly, concerns emerged among airlines and regulators regarding pilot skill decay as pilots lucky enough to still be able to fly had one or two rotation a month at most – except for cargo pilots. Less flights mean less opportunities for pilots to retain their skills. Therefore, a growing concern rapidly spread among aviation practitioners regarding the pandemic's impacts on lack of practice effects in flight operations.

2 RELATIVE WORK

2.1 Pandemic affecting pilots' skill decay

The COVID-19 pandemic's unpredictability led to challenging times for the aviation sector. It increased risks which had direct consequences on the aviation personnel, such as reduced wages and furloughs as well as increased health measures. These measures created new safety threats especially in terms of increased fatigue levels, and low morale which had a repercussion on the number of incidents in 2020 and 2021. Thus, skill degradation has become an important topic due to grounded aircraft and crews. Skills can be divided into two categories: soft skills (such as teamwork, decision-making abilities, and leadership) and hard skills (e.g., manual flying skills, aircraft systems and operational knowledge). Retention of skills among pilots is already well documented (e.g., Casner et al., 2014; Ebbatson et al., 2010; Hanusch, 2017). These studies mostly focus on hard skills decay (especially manual flying and knowledge about aircraft automation) although they also hint towards the implications on soft skills, as pilots' decision on using aircraft automation – and which mode / level they use – also depend on their set of soft skills. While hard skills can be retained longer and/or regained relatively fast (within a few flights / simulator sessions), soft skills are more difficult to retain and to build back up, as they depend not only on training but also on more complicated factors such as the operating environment, individual and crew experience (McCarthy & Agnarsson, 2018).

EASA and IATA published additional guidance for airlines on how to maintain flight crew proficiency in addition to the existing ICAO regulations (especially Annex 6) which requires at least three take-offs and three landings within the last ninety days. Subsequently, EASA determined that different types of decay can take place, including piloting skills decay and decay of aircraft specific knowledge and/or operational knowledge.

The consequences are multiple: there is the risk of a reduced adherence to Standard Operating Procedures (SOPs), an increase in slips, lapses, and data entry errors (EASA, 2021a). Performance in the cockpit has been found to be highly correlated to recent flying experience (Ebbatson et al., 2010), and to the type of flight operation (long-haul versus short-haul) (Haslbeck et al., 2018; Haslbeck & Hoermann, 2016). High workload phases in the cockpit usually occur when the aircraft is close to the ground, during take-off, approach, and landing. These phases require most of pilots' skills both in terms of communication and workload management but also on staying ahead of the aircraft (which are mostly soft skills). These characteristics are likely to degrade in case of a lack of recency especially in case of shorter approach paths (e.g., because of a shortcut given by Air Traffic Control), which requires more anticipation from the pilots. This is complicated further by flight deck automation, which can be simple in appearance but features complicated background processes. Advanced automation requires a higher level of cognitive skills from pilots to maintain aviation safety are required in case of unusual situations (such as malfunctions or input errors) due to the inherent complexity of the automated system (Casner et al., 2014). Operating a modern airliner can be depicted as joint cognitive system where distributed cognition takes place between the operators (the pilot-flying and pilot-monitoring) and the automation systems (which can be considered to hold functioning abilities).

2.2 The objectives of an FDM programme

In order to quantify and analyse safety performance, airlines typically rely on FDM / FOQA within their Safety Management System (SMS). It helps them identify operational risks which may require mitigating actions in the form of improved simulator training or revised SOPs for a specific aircraft type, operated in a specific airport or operational environment. FDM focuses on aircraft data (consisting of raw flight data analysis, such as altitude or speed deviations), which means it can be difficult to link a specific deviation directly to human performance. FDM as of today is based on capturing deviations from pre-set thresholds. Pilots' inputs (e.g., on the yoke / sidestick, rudder and throttle) are recorded, but it difficult to analyse the interactions between pilots in the cockpit, with ATC and their decision-making process behind these inputs solely through FDM (Maille, 2015; Stogsdill, 2021). Therefore, it is usual to combine FDM events with Air Safety Reports (ASRs) written by pilots to gain a broader understanding of a situation beyond the raw data (Walker, 2017). FDM can nevertheless help airlines and regulators analyse pilot proficiency. Deviations from acceptable values at stages of flight where the aircraft is either flown manually (such as unstable approaches, high pitch events, hard touchdowns) or where active decisions regarding the flight path need to be made (typically on approach and landing) can provide information about the pilots' flying skills (Bromfield & Landry, 2019). In addition, these flight phases require of a greater cognitive complexity for the crews when compared to other flight phases, and so require a great set of handling skills (Ebbatson et al., 2010). FDM deviations which can be related to pilots' flying skills can also have different causes, such as weather (windshear, runway conditions, ATC, etc.) Weather disruption, for example, can cause an increase in FDM occurrences which would normally be related to manual flying skills and could therefore bias the results (Schultz et al., 2018).

FDM analyses are typically performed within safety matrixes, which combines both event severity and frequency. Today's (2022) advances in flight safety research states that it is more beneficial to aim for a reduction in event severity rather than frequency (Holtom, 2007). In fact, recurring events with a low severity are preferable to less frequent events but with a much higher severity level and thus possible consequences. Safety knowledge gained prior to the pandemic helped the air transport sector to build up resilience which was used to cope with the pandemic's effects. By further developing and adjusting FDM to a more dynamic and changing environment, the pandemic can help increase the level of resilience, and thus the level of safety, as safety practitioners will be better prepared for tomorrow's threats.

In the past years, specific techniques in data analytics, deep-learning, and machine learning have been proposed to detect anomalies during flights. For example, Multiple-Kernel Anomaly Detection has been proposed by Matthews et al., (2014). It could combine information from different data sources and identify abnormalities within a flight; Another example is a clustering technique based on Gaussian Mixture Model (GMM) which was employed to detect unusual data patterns in flights, an indicator for increasing level of risks (Li et al., 2016); Other studies employed autoencoders, one of the powerful techniques in deep learning, to detect unknown hazards during the approach phase (Fernández et al., 2019). However, theses methods are still rarely used among airlines due to their complexity as well as difficulty to interpret the results.

3 METHOD

3.1 Data source

The data is composed of 4761 FDM occurrences out of 123'140 flights in total, retrieved from a major European airline between June 2019 and May 2021 (24 months) on the Airbus A320 family (ranging from A319 to A321) and Boeing B777 family (B772 & B777) which was first processed by the operator. The dataset (a .csv file) consists of a short event description along with several related pieces of information, such as the month and year of occurrence, the aircraft type, flight phase, place of occurrence and associated exceedance values. In addition, a severity index (SI) score is attributed to the event, based on an equation for each exceedance, in order to quantify its risks. The SI scale is continuous, and composed of natural numbers starting at 0. The higher the exceedance, the higher the associated severity index score. Each event is categorised depending on the occurrence type. In order to simplify the analysis, the events were classified into one of the main categories as mentioned in the EASA FDM recommended practices. These are Controlled Flight Into Terrain (CFIT), Loss of Control Inflight (LOCI), Mid-Air Collision (MAC) and Runway Excursion (RE). These criteria are based on EASA's standardised FDM framework (EASA, 2016). Due to confidentiality reasons, the data is only available to the authors and it is not possible to disclose a detailed description of the data nor for an external practitioner to replicate the analysis.

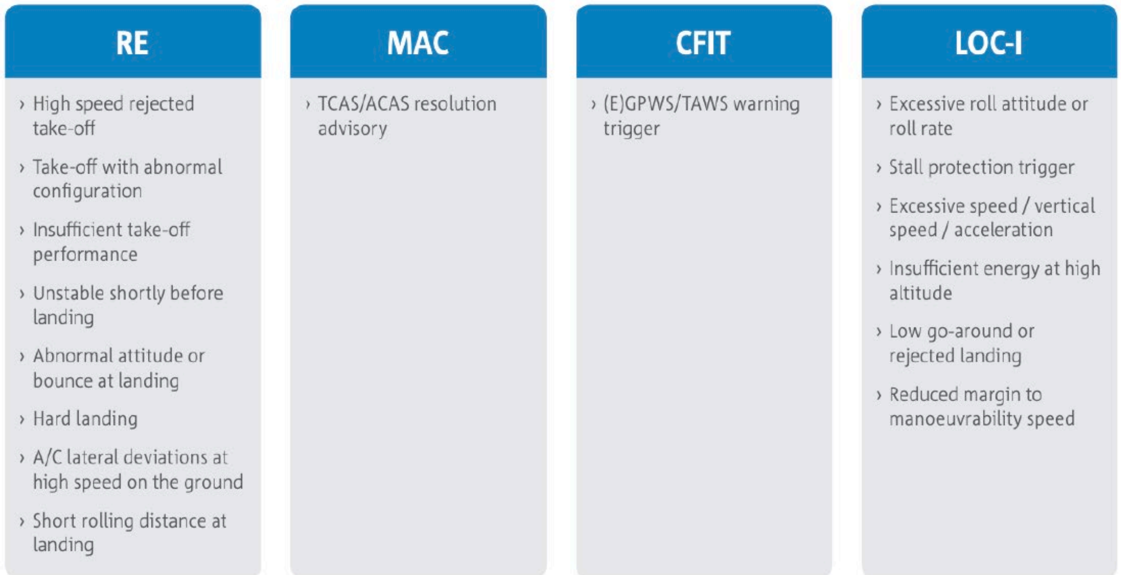

Figure 1: Summary of the main EASA FDM categories (EASA, 2016)

As the airline policy is to create an FDM event in case of Go-Around, another category was added, Go-Around (GA), to reflect this parameter. Go-arounds can have different causes. It can be due to ATC instructions, weather-related phenomena (such as windshear), or upon the crew's decision, for instance in case of an unstable approach. The dataset also comprises the flight phase (take-off, climb, cruise, descent, approach, landing, and go-around) at which the occurrence took place. It is worth to note that "go-around" can be an event category but also a flight phase.

3.2 Research procedure

The dataset has been divided into three stages, before pandemic (stage 1 - 06.2019-01.2020 – 2915 FDM events), beginning of pandemic (stage 2 - 02.2020-09.2020 – 1328 FDM events), and during pandemic (stage 3 - 10.2020-05.2021 – 518 FDM events). A significant drop in flight numbers occurred at the pandemic beginning in 2020 (26'128 flights at stage 2 compared to 82'819 flights at stage 1) which continued at stage 3 (14'193 flights). Two statistical analyses were performed, event frequencies and severity index, while including different variables, the five event categories, seven flight phases and five fleets. Focus was set on specific markers (e.g., RE, and LOC-I categories) which are directly related to manual flying skills (EASA, 2016). R version 4.0.3 (R Core Team, 2020) and RStudio interface version 1.3.1093 were used.

Table 1: Number of FDM events for each category and pandemic stage

	Stage 1	Stage 2	Stage 3	Total
CFIT	197	81	29	307
LOC-I	576	261	58	895

MAC	128	28	17	173
RE	1360	667	300	2327
GA	654	291	114	1059
Total	2915	1328	518	4761

3.3 Statistical tools used

Occurrence frequencies (number of occurrences divided by the total number of flights for each group), means, medians and standard deviations of different variable groups (such as the severity index) were calculated as part of the exploratory data analysis. P-values of less than 0.05 were regarded as statistically significant (Field, 2018). Chi-Square tests were used for analysing the FDM occurrence frequencies for each stage. The Chi-square test is a non-directional test which aims at determining whether the observed frequencies are below or above corresponding expected frequencies. The dependent variables here represent the frequency data for each FDM category, flight phase and fleet. If an association is significant, the counts in each cell was examined further in order to determine if it is larger or smaller than the expected value by testing standardized Pearson residuals (Agresti, 2002). Absolute values of standardized Pearson residuals that are more than 1.96 suggested a significant difference with a significant level at 0.05. For the SI analysis, the objective is to assess the interaction effects between the pandemic stages and FDM events based on the severity index score. Following an explanatory data analysis, Levene's test was performed on the SI index scores which suggested heterogeneity, therefore a Welch-ANOVA and following Games-Howell test was applied for the post-hoc analysis.

4. RESULTS

4.1 Testing associations between three stages of pandemic and five FDM categories

The results demonstrate a significant association between the three pandemic stages and five FDM categories, χ 2 (8, N = 4761) = 19.06, $p < 0.05$ (figures 2 & 3). A Welch-ANOVA and Games-Howell post-hoc tests were conducted for the event categories. The results demonstrate a significant increase in event severity after the first pandemic stage for LOC-I and for RE events (F (4, 4761) = 789.86, p < 0.001, table 2) but not for the other event categories. It is worth to note that not only all event frequencies (except Mid-air collisions) increased at the pandemic beginning, but so did their severity index score as well (however, only significantly for LOCI and RE events).

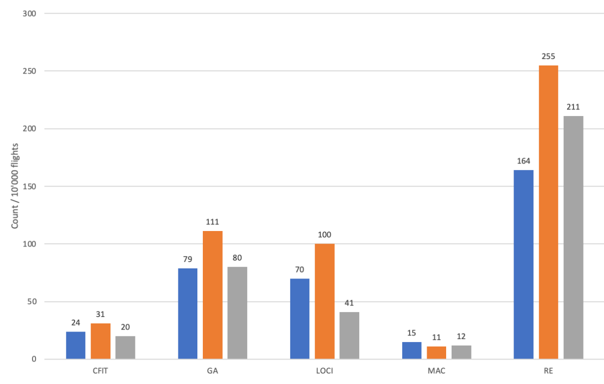

Figure 2: FDM event frequencies associated with the five FDM categories among the three pandemic stages.

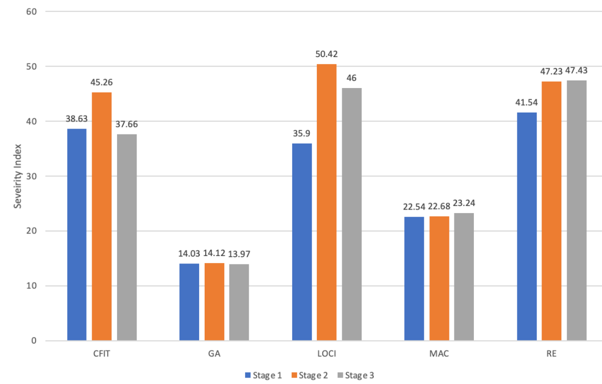

Figure 3: Severity index scores of FDM exceedances on five event categories across the three stages pandemic

Table 2: Mean severity index scores and significant results for LOC-I and RE event categories

Event Category	**Stage 1 Before pandemic**	**Stage 2 Pandemic beginning**	**Stage 3 During pandemic**	**Significance between stages**
	Average SI (M & SD)	Average SI (M & SD)	Average SI (M & SD)	Significant stages are displayed only if p < 0.05
CFIT	38.63(24.85)	45.26(32.47)	37.66(20.82)	No significance (p > 0.05)
LOCI	35.90(27.44)	50.42(34.35)	46.00(35.20)	Stage 1 vs. Stage 2 **** (p < 0.001)
MAC	22.54(2.51)	22.68(2.54)	23.24(2.46)	No significance (p > 0.05)
RE	41.54(27.95)	47.23(33.28)	47.43(31.64)	Stage 1 vs. Stage 2 *** (p = 0.001) Stage 1 vs. Stage 3 ** (p < 0.05)
GA	14.03(0.61)	14.12(2.11)	13.97(1.67)	No significance (p > 0.05)

4.2 Testing associations between the three stages of the pandemic and seven flight phases

The results demonstrate a significant association between the three pandemic stages and seven flight phases, χ^2 (10, N = 4761) = 31.27, $p < 0.01$. The bar charts on figures 4 and 5 show the weighted values of FDM events on the three stages of pandemic as well as their associated severity index scores. The Welch-ANOVA and subsequent Games-Howell post-hoc tests for the severity index scores (F (6, 4761) = 198.12, p < 0.001, table 3) demonstrate significant increases for events occurring on take-off, approach, landing, and for go-arounds. It is to note that the number of events on the climb phase was too low to draw any conclusion.

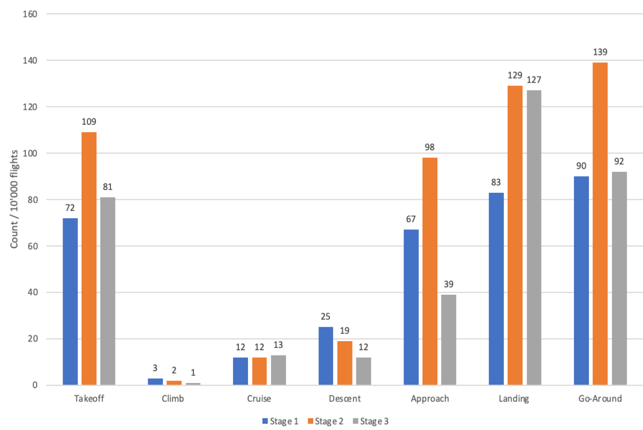

Figure 4: FDM event frequencies associated with the seven flight phases among the three pandemic stages.

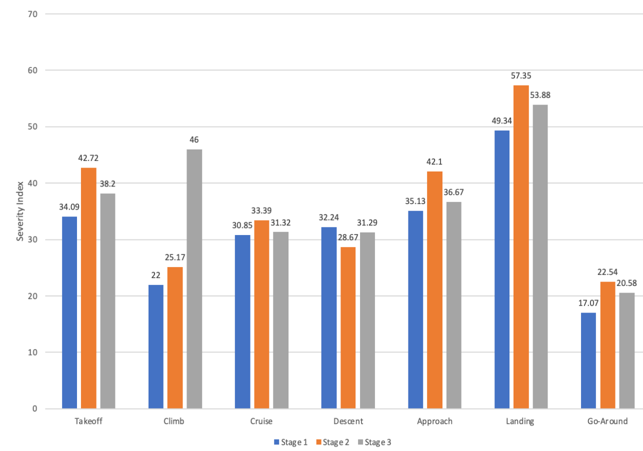

Figure 5: Severity index scores of FDM events on seven flight phases across the three pandemic stages

Table 3: Severity index scores and significance levels for events depending on flight phase

Flight Phase	**Stage 1 Before pandemic**	**Stage 2 Pandemic beginning**	**Stage 3 During pandemic**	**Significance between stages**
	Average SI (M & SD)	Average SI (M & SD)	Average SI (M & SD)	Significant stages are displayed only if p < 0.05
TO	34.09(24.53)	34.09(24.53)	34.09(24.53)	Stage 1 vs. Stage 2 *** (p < 0.001)
CLB	22.00(8.40)	25.17(9.20)	46.00(NA)	FDM event numbers too low to draw significance
CRZ	30.85(20.89)	33.39(19.92)	31.32(22.75)	No significance (p > 0.05)
DES	32.24(18.05)	28.67(14.19)	31.29(17.05)	No significance (p > 0.05)
APP	35.13(27.13)	42.10(29.43)	36.67(26.80)	Stage 1 vs. Stage 2 ** (p < 0.005)
LDG	49.34(29.16)	57.35(34.15)	53.88(31.85)	Stage 1 vs. Stage 2 *** (p < 0.001)
GA	17.07(13.35)	22.54(23.94)	20.58(21.54)	Stage 1 vs. Stage 2 *** (p < 0.001)

4.3 Testing associations between three stages of pandemic and flight type

The results demonstrate a significant association between the three pandemic stages and flights on short-haul aircraft, χ^2 (2, N = 4761) = 76.22, $p < 0.001$. The bar charts on figures 5 and 6 show the weighted values of FDM events on the three stages of pandemic, which could be interpreted as the number of events for 10,000 flights based on chi-square tests, as well as their associated severity index scores. The results demonstrate a significant increase in both event frequency and severity index for short-haul aircraft (A319, A320, and A321) (F (2,803.74) = 22.96, $p < 0.001$, table 4) before and during the pandemic compared to a pre-pandemic level. This increase is also present on long-haul aircraft (B773 and B777); however, it is not significant ($p > 0.5$).

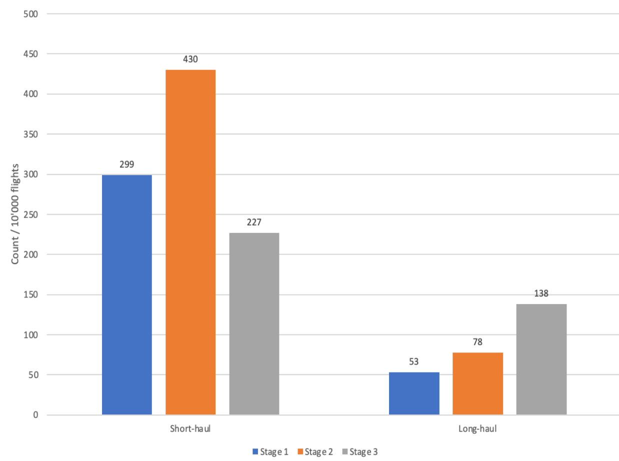

Figure 6: FDM event frequencies associated with the flight type among the three pandemic stages.

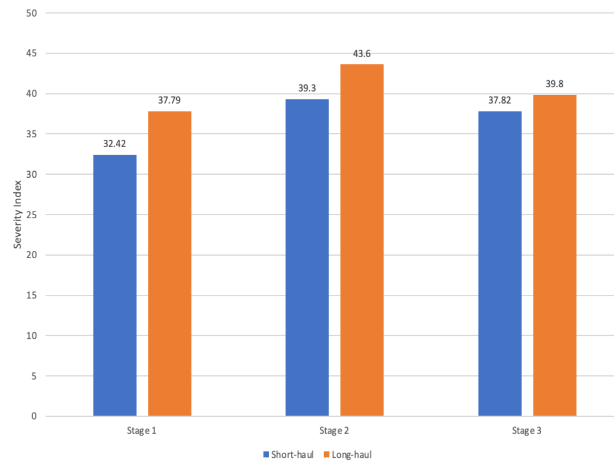

Figure 7: Severity index scores of FDM exceedances on the two flight operation types across the three pandemic stages

Table 4: Mean severity index scores and significance levels for events on based on short-haul and long-haul aircraft

Flight operation type	Stage 1 Before pandemic	Stage 2 Pandemic beginning	Stage 3 During pandemic	Significance between stages
	Average SI (M & SD)	Average SI (M & SD)	Average SI (M & SD)	Significant stages are displayed only if $p < 0.05$
SH	32.42(25.06)	39.30(31.82)	37.82(30.33)	Stage 1 vs. Stage 2 **** ($p < 0.001$) Stage 1 vs. Stage 3 ** ($p < 0.01$)
LH	37.79(30.72)	43.60(35.67)	39.80(30.93)	No significance ($p > 0.05$)

6. DISCUSSION

6.1 A rise in runway excursion and loss of control in-flight precursors as the pandemic spread

The results demonstrate that the pandemic had an effect on pilot proficiency, the effect being different across the pandemic stages and across fleets. Hence, the significant frequency increase in LOC-I and RE event as well as their significant increase in severity score can be linked back to the pandemic's effects. Runway excursion events in particular, can demonstrate a decay in flying proficiency among pilots, as this type of event is directly related to flying skills (for instance a hard landing or high pitch attitude on take-off) (EASA, 2021b). This finding is consistent with previous studies which spotted two effects of unregular flying on pilots with two different temporalities. The first direct effect of a prolonged period without flying has been identified as a decrease of manual flying skills (Ebbatson et al., 2010; Mizzi et al., 2022), which is shown here by the increase both in RE events and associated severity score at the pandemic beginning. The second and more latent effect of grounding among pilots is a memory and practice deterioration of knowledge about aircraft systems, procedures, cockpit flows and soft skills. As the pandemic spread, airlines were forced to shift towards increased cost-efficiency, and it can be argued that although simulator practice sessions were implemented, not all flight crews could not maintain their level of thoroughness due to lack of recency since the beginning of the pandemic. Although difficult to determine through FDM, a decay in soft skills may also have taken place, which could have had an influence on the increase of LOC-I and RE event frequencies and severity. Flight path management does not only depend on piloting skills but also on crew performance in terms of various skills such as anticipation, and decision-making for instance (Flight Safety International, 2014; Sumwalt et al., 2015). Recent incidents have been reported where a fade in soft skills might have taken place (e.g., AAIB, 2021; BEA, 2022). Moreover, it has been determined that pilots did not necessarily proactively engage themselves in maintaining their core competencies due to the uncertainties about their future while being grounded (Mizzi et al., 2022). Thus, pilots can find it more difficult to carry out some tasks when flying again, or may carry tasks out in the wrong sequence (incorrect cockpit flow). This can have the consequence of increasing the rate of slips, lapses, and input errors into the cockpit automation (CAA, 2021). This effect is more insidious, as manual flying skills can be regained pretty quickly (after a couple of flights) following a prolonged period without flying (Mizzi et al., 2022). It can be further exacerbated by the operating environment: as less flights were operated; aircraft were more prone to get shortcuts and shorter approaches increasing the risks of performing unstable approaches if not anticipated by the crew. RE events typically occur on flight phases close to the ground (take-off, approach, landing, and go-around). These flight phases are the busiest phases for pilots.

6.2 In addition to a significant increase of FDM events occurring "close to the ground"

The results demonstrate that both the frequencies and severity index scores of events occurring close to the ground increased. These flight phases are the ones where pilots' mental workload is the highest due to the larger number of tasks they have to perform (flying the aircraft, acknowledging Air Traffic Control clearances, actively managing the aircraft automation, etc.) and where the situation is the most changeable (Metalis, 1991; Stimpson et al., 2016). Short term instructions from ATC, changes in aircraft configuration (flaps, gear), altitude and speeds require higher cognitive attentional levels and planning ahead capacity than other flight phases such as cruise. It is expected that a decrease in operational procedure retention skills will have a negative effect on events occurring during these flight phases (Ebbatson et al., 2010; Hendrickson et al., 2006). Thus, the increase in event frequencies and severities on these close-to-the-ground flight phases can be associated with both a decrease in manual flying abilities and a decrease in pilots' operational proficiency which shows up during the take-off, approach, and landing flight phases. Although the average severity index scores remain higher at the third stage (during pandemic) than at the first stage (before pandemic), the mean event frequencies tend to decrease at the third stage (figure 5 and table 3). This could indicate a resilient behaviour among the airline and pilots and the effectiveness of the implemented pilot training sessions to cope with the degraded rosters on a medium term.

6.3 And an immediate effect on short-haul pilots' proficiency versus a more latent effect on long-haul pilots' proficiency

However, short-haul and long-haul pilots seem to have been affected differently in terms of proficiency decay and with different temporalities. The increase in FDM event frequency and severity, although present for short-haul and long-haul pilots is only significant for short-haul pilots. This can be explained by the fact that short-haul pilots were affected more immediately by the pandemic's effects and border closures than long-haul pilots who were still able to fly more cargo instead of passengers. However, the short-haul sector was able to recover in the third pandemic stage, by reducing the FDM event frequencies and settling even if the increase in severity index scores still remains higher and significant. It shows that the Computer-based training (CBT) and simulator sessions provided by the airline effectively addressed the competencies affected by skill fade. Besides training hard skills (manual flying skills), the airline was able to effectively train also soft skills which are highly correlated with high performing crews (McCarthy & Agnarsson, 2018; Mizzi et al., 2022). In contrast, it can be hypothesised that long-haul pilots were also affected by the pandemic effects, but in a more latent and insidious way, as they were able to retain a lower albeit acceptable level of recent experience. On the third stage however, the long-haul severity index scores remained higher than before the pandemic while the event frequencies almost doubled (figures 6 & 7 and table 4). In overall, the severity index scores are higher on long-haul than on short-haul aircraft. The reason for this difference could not be determined from the dataset, however, it could be linked to the fact that long-haul pilots have got less opportunities to practice their hard and soft skills than short-haul pilots as they typically operate less flights. Finally, it would prove to be beneficial to extend the timeframe of this study to assess whether this increase in event frequencies continued towards the end of 2021 or if it was only temporary.

6.4 Limitations

Some limitations occurred as part of this study, considering the dataset being limited to 24 months. Firstly, it was not possible to examine the effects of weather (storms, winds, etc.) on the FDM events, although these can have an influence, especially in relation to go-arounds and runway excursions risks. Secondly, it was not possible to analyse events beyond the FDM data with the crew's reports as text ASRs were not added to the dataset. An FDM event is only represented by its recorded data and processed exceedances. Without the crew's perspective, it can be difficult to determine the reasons behind specific actions, i.e., the crew's decision-making process. Finally, each recorded parameter was processed using a specific threshold and algorithm on different types of aircraft specific to the company algorithm, which due to confidentiality reasons, lacks in transparency.

7. CONCLUSION

Did the COVID-19 pandemic rust pilots' skills? A short, straightforward answer would be: yes. The FDM data shows that events directly related to pilot skills (such as runway excursions precursors) significantly increased both in terms of frequency and in terms of severity during the pandemic. These increases were prominent on flight phases close to the ground (take-off, approach, and landing), where workload and mental demands are the highest. However, skill decay occurred differently depending on the pandemic stages and on the fleets (whether short-haul or long-haul). Skill decay affected pilots both in terms of loss of manual flying skills and in terms of routine decay in using operational procedures and loss of knowledge as well as soft skills. The decrease in hard skills has shown to be present in the early pandemic stages, especially for short-haul pilots who flew the less due to the heavy drop in flight numbers. While they were able to pretty rapidly regain their manual flying skills, the fade in operational knowledge and routine as well as soft skills appears more latent and to last longer. This effect appears less marked for long-haul pilots who were still able to fly at a relatively regular rate, however they seem to be affected as well by routine fade, though in a less noticeable way. Finally, the expected overall drop in aviation safety back in 2020 due to the disruptions did not occur (even though some incidents / accidents were clearly linked the effects of the pandemic). This demonstrates that the aviation system (comprising pilots, ATC, regulators, airlines, manufacturers, etc.) showed resilience and were able to effectively implement mitigation measures such as enhanced training sessions to counteract the negative pandemic effects.

8. REFERENCES

AAIB. (2021). *Special Bulletin S2/2021*. https://www.gov.uk/aaib-reports/aaib-special-bulletin-s2-slash-2021-on-boeing-737-8k5-g-fdzf

Agresti, A. (2002). *Categorical Data Analysis* (3rd Edition). John Wiley & Sons, Inc. https://doi.org/10.1002/0471249688

BEA. (2022). *Incident to the Airbus A318-100 registered F-GUGM operated by Air France on 12/09/2020 at Paris-Orly (Val-de-Marne)*. https://bea.aero/en/investigation-reports/notified-events/detail/incident-to-the-airbus-a318-registered-f-gugm-operated-by-air-france-on-12-09-2020-near-paris-orly/

Bromfield, M. A., & Landry, S. J. (2019). Loss of control in flight – time to re-define? *AIAA Aviation 2019 Forum*, 1–10. https://doi.org/10.2514/6.2019-3612

CAA. (2021). *Safety Notice, Awareness of Skill Fade and Suggested Mitigations*. https://publicapps.caa.co.uk/docs/33/SafetyNotice2021011.pdf

Casner, S. M., Geven, R. W., Recker, M. P., & Schooler, J. W. (2014). The retention of manual flying skills in the automated cockpit. *Human Factors*, *56*(8), 1506–1516. https://doi.org/10.1177/0018720814535628

EASA. (2016). *Developing standardised FDM-based indicators*. https://www.easa.europa.eu/sites/default/files/dfu/EAFDM__standardised_FDM-based_indicators_v2_Ed2017.pdf

EASA. (2021a). *Review of Aviation Safety Issues Arising from the COVID-19 Pandemic*. https://www.easa.europa.eu/downloads/127172/en

EASA. (2021b). *Safety Issue Report - Skills and Knowledge Degradation due to Lack of Recent Practice*. https://www.easa.europa.eu/community/topics/skills-and-knowledge-degradation

Ebbatson, M., Harris, D., Huddlestone, J., & Sears, R. (2010). The relationship between manual handling performance and recent flying experience in air transport pilots. *Ergonomics*, *53*(2), 268–277. https://doi.org/10.1080/00140130903342349

Fernández, A., Martínez, D., Hernández, P., Cristóbal, S., Schwaiger, F., María Nuñez, J., & Ruiz, J. M. (2019). Flight Data Monitoring (FDM) Unknown Hazards detection during Approach Phase using Clustering Techniques and AutoEncoders. *9th SESAR Innovation Days*.

Field, A. (2018). Discovering Statistics with IBM and SPSS. In *Sage* (5th ed.). SAGE Publications Ltd.

Flight Safety International. (2014). *A Practical Guide for Improving Flight Path Monitoring*. https://flightsafety.org/files/flightpath/EPMG.pdf

Hanusch, M. (2017). *Manual Flying Skills-Airline Procedures and their Effect on Pilot Proficiency Human Factors Approaches and Models in LOC-I Accident Analysis and Prevention*. https://doi.org/10.13140/RG.2.2.17886.23362

Haslbeck, A., Hoermann, H. J., & Gontar, P. (2018). Stirring the Pot: Comparing Stick Input Patterns and Flight-Path Control Strategies in Airline Pilots. *International Journal of Aerospace Psychology*, *28*(1–2), 15–30. https://doi.org/10.1080/24721840.2018.1481343

Haslbeck, A., & Hoermann, H.-J. (2016). Flying the Needles: Flight Deck Automation Erodes Fine-Motor Flying Skills Among Airline Pilots. *Human Factors*, *58*(4), 533–545. https://doi.org/10.1177/0018720816640394

Hendrickson, S. M. L., Goldsmith, T. E., & Johnson, P. J. (2006). Retention of Airline Pilots' Knowledge and Skill. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *50*(17), 1973–1976. https://doi.org/10.1177/154193120605001755

Holtom, M. (2007). *FOQA - Flight Data Analysis of Aircraft for Flight Safety*. PIA Air Safety Publication. https://www.theairlinepilots.com/forumarchive/flightsafety/foqaflightdataanalysis.php

IATA. (2018). *IATA Forecast Predicts 8.2 billion Air Travelers in 2037*. https://www.iata.org/en/pressroom/pr/2018-10-24-02/

Li, L., Hansman, R. J., Palacios, R., & Welsch, R. (2016). Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring. *Transportation Research Part C: Emerging Technologies*, *64*, 45–57. https://doi.org/10.1016/j.trc.2016.01.007

Maille, N. (2015, July). On the use of Flight Operating Procedures for the Analysis of FOQA data. *6th European Conference for Aeronautics and Space Sciences (EUCASS)*. https://www.researchgate.net/publication/314973879

Matthews, B., Das, S., Bhaduri, K., Das, K., Martin, R., & Oza, N. (2014). Discovering Anomalous Aviation Safety Events Using Scalable Data Mining Algorithms. *Journal of Aerospace Information Systems*, *11*(7), 482–482. https://doi.org/10.2514/1.I010211

McCarthy, P., & Agnarsson, A. (2018). Pilot performance assessment in simulators: exploring alternative assessment methods. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *10906 LNAI*, 615–636. https://doi.org/10.1007/978-3-319-91122-9_50/FIGURES/14

Metalis, S. A. (1991). Heart Period as a Useful Index of Pilot Workload in Commercial Transport Aircraft. *The International Journal of Aviation Psychology*, *1*(2), 107–116. https://doi.org/10.1207/s15327108ijap0102_2

Mizzi, A., Lohmann, G., & Carim Junior, G. (2022). The Role of Self-Study in Addressing Competency Decline Among Airline Pilots During the COVID-19 Pandemic. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 001872082211136. https://doi.org/10.1177/00187208221113614

R Core Team. (2020). *R: A Language and Environment for Statistical Computing*. https://www.R-project.org/

Schultz, M., Lorenz, S., Schmitz, R., & Delgado, L. (2018). Weather Impact on Airport Performance. *Aerospace*, *5*(4), 109. https://doi.org/10.3390/aerospace5040109

Shepardson, D. (2018, January 1). 2017 safest year on record for commercial passenger air travel: groups. *Reuters*. https://www.reuters.com/article/us-aviation-safety-idUSKBN1EQ17L

Stimpson, A. J., Ryan, J. C., & Cummings, M. L. (2016). Assessing Pilot Workload in Single-Pilot Operations with Advanced Autonomy. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *60*(1), 675–679. https://doi.org/10.1177/1541931213601155

Stogsdill, M. (2021). When Outcomes are not Enough: An Examination of Abductive and Deductive Logical Approaches to Risk Analysis in Aviation. *Risk Analysis*. https://doi.org/10.1111/RISA.13681

Sumwalt, R., Cross, D., & Lessard, D. (2015). Examining How Breakdowns in Pilot Monitoring of the Aircraft Flight Path. *International Journal of Aviation, Aeronautics, and Aerospace*, *2*(3), 8. https://doi.org/https://doi.org/10.15394/ijaaa.2015.1063

Walker, G. (2017). Redefining the incidents to learn from: Safety science insights acquired on the journey from black boxes to Flight Data Monitoring. *Safety Science*, *99*, 14–22. https://doi.org/10.1016/j.ssci.2017.05.010