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Abstract

This study investigated burnout related to emotions in three categories of pilots: commercial passenger, commercial cargo, and military. While pilot burnout has been previously studied, challenges in self-reporting limit understanding. This study extends previous research by analyzing pilots' anonymous online forum posts to gain insight into burnout-related emotions. Natural Language Processing was conducted with the $RoBERTa-base-go\_emotions$ model, which analyzed 1,130,530 online forum posts from commercial passenger, commercial cargo, and military pilots for 27 emotion categories and one absence of emotion category (i.e., neutral). An exploratory composite score reflecting burnout-related emotional expression was calculated using seven emotions associated with burnout. ANOVAs compared emotion levels across pilot groups. "Neutral" was the predominant category across all pilot groups, followed by curiosity and approval. Statistically significant differences were found between pilot groups for all emotions, and "neutral" effect sizes were consistently trivial in magnitude (Cohen's $f < 0.1$). The same trivial magnitude level effect size was encountered with the burnout score. As such, despite the ubiquitous presence of statistical significance across variables, the obtained effect sizes suggested practical equivalence amongst the three pilot groups. The prevalence of neutral language and minimal differences between pilot groups may reflect a professional culture discouraging open expression of negative emotions. These findings suggest further investigation into how aviation culture influences emotional expression, burnout presentation, and the reporting of burnout among pilots.

Keywords: *Pilot Burnout, Emotion Analysis, Online Discourse, Natural Language Processing, Aviation Psychology*

Introduction

The career of an aviation pilot is often perceived as prestigious and fulfilling. However, behind the glamorous reputation, aviators are often confronted with significant stress factors that can profoundly impact their physical and mental health. The challenges of carrying the responsibility for safely transporting human lives and property, unpredictable schedules, and navigating adverse weather conditions create demanding roles that make pilot positions highly difficult, often resulting in burnout (Demerouti et al., 2019; Fanjoy et al., 2010). Burnout among pilots can negatively affect mental and physical health, job contentment, and overall well-being, which could pose a danger to airline safety due to potential increases in human error (Kizilcan & Mizrak, 2022). Due to the negative consequences of pilot burnout on both pilots and the public, it is imperative to deepen the understanding of burnout within the aviation industry. The purpose of the current study was twofold: (a) to identify gaps in the current research on pilot burnout and (b) to produce preliminary knowledge about emotional indicators of burnout that may contribute to informing policies and procedures in the aviation profession.

Understanding pilots' burnout symptoms is challenging due to disclosure risks. Federal regulations require pilots to report medical and psychological conditions (14 C.F.R. § 67.10, 2023). Recent Federal Aviation Administration (FAA) changes (2024) now allow some mental health diagnoses without the risk of disqualification, aiming to destigmatize mental health issues in aviation. Despite low disqualification rates for mental health reports (Federal Aviation Administration [FAA], 2023b), many pilots still withheld information due to career concerns (Hoffman et al., 2022, 2023). The impact of these recent changes remains unclear. This study uses Natural Language Processing (NLP) analysis of pilots' online

discourse to provide preliminary insights into emotional aspects of burnout in this population.

Relevant Literature

An examination of the existing literature on this topic revealed six key features: an overview of burnout; emotions associated with burnout; mental health and burnout among pilots; burnout differences among pilot types (passenger, cargo, military); online discourse for burnout-related experiences; and NLP for evaluating online discourse.

For decades, extensive research has been conducted on the many emotions that contribute to burnout. Researchers have continuously attempted to understand the contributing factors and fundamental emotions associated with the phenomenon of burnout using measurement tools such as the Maslach Burnout Inventory (Maslach et al., 1996), which explores emotional exhaustion, depersonalization, and personal accomplishments, and the Oldenburg Burnout Inventory (Demerouti & Bakker, 2008), which measures exhaustion and disengagement. Despite these efforts, the absence of a clinically defined set of symptoms, behaviors, and experiences that are specific to burnout and universal to the health-related professions makes it difficult to assess (Bianchi et al., 2019). Tavella et al. (2020) attempted to measure and define burnout by carefully examining work-focused factors and those surrounding the inability to feel, further highlighting the challenges in assessing this complex phenomenon. The most advanced theory we encountered in our review was that of Wilmar Schaufeli and his Burnout Assessment Tool (BAT) model. His theory and psychometric investigations found a four-facet model of a burnout syndrome: (1) exhaustion (i.e., a severe loss of energy that results in feelings of both physical and mental exhaustion); (2) mental distance (i.e., a strong reluctance or aversion to work, indifference, and cynicism); (3) cognitive impairment (i.e., memory problems, attention and concentration deficits, and poor cognitive performance); and (4) emotional impairment (i.e., intense emotional reactions such as anger or sadness, and feeling overwhelmed by one's emotions; Schaufeli and De Witte, 2023, p. 4).

As Schaufeli and De Witte (2023) pointed out, burnout is a complex phenomenon with varying definitions and often confounded with other psychological phenomena. While structured inventories reliably assess professional burnout, specific emotions can also characterize this phenomenon. Burnout is associated with anxiety, anger, apathy, and dejection (McNeill et al., 2018). Disappointment predicts burnout-related emotional exhaustion (Silva & Menezes, 2008). Fear of failure increases psychological stress and burnout risk (Lemyre et al., 2008), while fear of shame correlates with higher stress and reduced accomplishment (Gustafsson et al., 2017). Sadness strongly correlates with burnout (Atmaca et al., 2020). Disgust has been positively associated with emotional exhaustion and the intention to leave a profession (Goerdeler et al., 2015). Annoyance influences burnout, affecting perceptions of annoying behaviors (Harrad & Sulla, 2018). Throughout the literature, these seven specific emotions (anxiety, anger, disappointment, fear, sadness, disgust, and annoyance) show strong associations with burnout, suggesting these emotional markers may serve as linguistic indicators for exploring burnout experiences in high-stress professions, such as aviation pilots.

Research within the aviation industry has highlighted the critical intersection of mental health and burnout among pilots (Cahill et al., 2018; Chang et al., 2023). There has been a growing recognition of the unique stressors faced by aviation professionals, including irregular work schedules, prolonged time away from home, and high responsibility of ensuring passenger and flight crew safety. Studies exploring the psychological impacts and stressors associated with burnout symptoms highlight the implications of untreated mental health issues on flight safety and emphasize the need for proactive measures to address pilot well-being (Cahill et al., 2020; Venus & grosse Holtforth, 2021). These studies emphasize the complexities surrounding pilot mental health and burnout. By examining the current research on pilot mental health and burnout, it becomes evident that these issues can impact the safety and efficiency of air travel and the long-term health and satisfaction of pilots. Given these complexities and safety implications, conventional research methods deserve reexamination. Prior studies have mostly used structured inventories to gauge burnout. However, these instruments struggle to fully capture the complexities of the experience of burnout, particularly in occupations where disclosure carries risks. Examining pilots' online discourse provides a promising way to study how burnout appears in this demographic, given the particular regulatory restrictions surrounding mental health disclosure. The development of NLP models allows for a method to analyze this language, which may uncover trends in pilots' experiences and descriptions that conventional assessment methods would miss. While the subject of burnout, fatigue, and work-related stress among pilots has garnered considerable scholarly attention (Cahill et al., 2021; Chang et al., 2023; Cullen et al., 2021; Demerouti et al., 2019; Fanjoy et al., 2010; Venus & grosse Holtforth, 2021, 2022), there remains a notable lack of comparative analyses between commercial passenger, commercial cargo, and military pilot groups. A more nuanced understanding of how burnout may be experienced between pilot groups, based on the variations in responsibilities, training protocols, organizational culture, and work/life balance, could assist in making recommendations to prevent burnout and work-related stress. However, no studies to date have examined the

differences between all three categories of pilots. Furthermore, varied terminology used to define commercial pilot groups, such as "professional" and "civilian" in existing studies (Martinussen et al., 2022; Minoretti & Emanuele, 2023; Olaganathan et al., 2021) does not allow for a clear distinction between passenger and cargo carrier pilots. The combined classification of commercial pilots in scholarly literature presents challenges in ascertaining nuanced differences in pilots' experiences of emotions associated with burnout based on employment categorization. The gap in the literature indicates that further investigation is needed to more accurately examine the experience of burnout between the three pilot cohorts.

Online discourse offers a pivotal method for individuals, including aviation professionals, to express and disclose emotions associated with burnout or mental health (Lachmar et al., 2017; Makita et al., 2021). Online platforms offer anonymous accessibility for pilots to share their experiences, challenges, and personal struggles related to their profession. This provides a unique insight into the emotional landscape of pilots dealing with occupational burnout and allows for a candid exploration of burnout signs and symptoms, potential coping mechanisms, and the search for support within the profession. Recent studies in professions such as software engineering and cybersecurity suggest that online discourse provides further insight into job fatigue and burnout (Nobles, 2022; Raman et al., 2020). Pilots' utilization of online discourse is a valuable source of information, offering authentic disclosures of burnout-related experiences and emotions. Researcher analysis of this discourse may provide a deeper understanding of pilots' emotions and stressors and potentially enrich academic knowledge of burnout.

NLP offers a set of tools uniquely suited to analyzing online discourse. NLP and machine learning technologies can produce nuanced emotional analyses that offer insight into online forum users' emotional and psychological states (Sailunaz et al., 2018). NLP tasks have significantly advanced because of breakthroughs in machine learning technologies and the emergence of bidirectional encoder representations from transformers (BERT). BERT is an advanced NLP model that evaluates text by examining words within their entire context. It simultaneously processes text from both directions, enhancing its grasp of meanings and word relationships. This comprehension is built through thorough pre-training and text prediction tasks (Devlin et al., 2018). For example, Wahiduzzaman et al. (2024) demonstrated BERT's utility and efficacy in analyzing emotional expressions in online forum posts. Similarly, Nijhawan et al. (2022) demonstrated the utility of BERT in detecting stress by classifying emotional markers such as joy, sadness, neutrality, fear, and anger from social media data. Leveraging BERT models can provide valuable perspectives that can be gained through the analysis of large-scale anonymous pilot online discourse and may be used to inform initiatives to enhance pilot well-being. However, while BERT models excel at identifying nuanced emotional markers in natural language, these linguistic patterns cannot be directly aligned with established burnout frameworks. Current burnout models describe a multifaceted experience encompassing cognitive, emotional, and physiological dimensions, complexities not fully captured by BERT models. Thus, the NLP driven analyses contained in research questions 3 and 4 below should be considered provisional efforts aimed at advancing the nomothetical net in pilot burnout research, rather than definitive mappings of emotional language to clinical constructs.

Statement of Research Questions

After a comprehensive literature review on pilot mental health and burnout, this study sought answer the following research questions (RQs):

- **RQ1:** What are the levels of emotions expressed in pilots' online discourse?
- **RQ2:** Do the levels of emotions expressed in pilots' online discourse differ based on whether the pilot is a commercial passenger, commercial cargo, or military pilot?
- **RQ3:** What is the level of burnout reflected in the language used in pilots' online discourse?
- **RQ4:** Does the level of burnout reflected in pilots' online discourse differ based on whether the pilot is a commercial passenger, commercial cargo, or military pilot?

These research questions were pre-registered at: https://osf.io/hgaz6/ After preregistration, some non-substantive word changes were made to RQ1 to be parallel with the wording of RQ2, RQ3, and RQ4.

Method

Design

This study used an NLP and emotion analysis design to categorize language in pilot online forum posts across 27 domains of emotions and the absence of emotion (neutral) using a multilabel classification model known as $RoBERTa-base-go\_emotions$ (Lowe, 2023). Online forum posts were written in English. Three variables were identified for this study: (a) $RoBERTa$ score, (b) emotion, and (c) pilot categories. Regarding the level of measure, the first variable was continuous, while the second and third were nominal. The unit of analysis was tokens, which $RoBERTa$ Tokenizer determined from the pretrained $RoBERTa-base-go\_emotions$ model (Lowe, 2023). This manuscript was submitted to the University

of Nevada, Reno Institutional Review Board, proposal number 2174745-2, and was assigned a determination of exempt status in accordance with federal regulations. A study methodology flowchart can be found in Figure 1 (see Appendix A).

A power analysis was done before the start of the study to determine the minimum sample size needed for sufficient power. The appropriate effect size for input was Cohen's f, expressed as a square root of mean squared difference divided by variance (Selya et al., 2012). A medium effect size for this power analysis was used (Cohen's f = .25; Cohen, 1988). To do the analysis, G*Power 3.1 was used (Faul et al., 2007) with the following inputs: (a) test family = F tests; (b) statistical test = ANOVA; (c) power analysis = *a priori*: compute required sample size - given α; power, and effect size; (d) effect size f = 0.25; (e) α error probability = .05; (f) power (1-β error probability) = 0.80; and (g) number of groups = 3. The G*Power 3.1 output parameters were (a) total sample size = 156 and (b) actual power = 0.80.

Study Corpus

Register, Scope, and Sources

The register was spoken language, and the subregister was pilot blogging. The source was online posts from Airline Pilot Central Forums, a well-respected aviation forum for pilots sponsored by AirlinePilotCentral.com (https://www.airlinepilotforums.com). The scope encompassed publicly available posts across three subforums: Major (commercial passenger), Cargo (commercial cargo), and Military. The data ranged from February 18, 2005, to April 8, 2024. The total number of posts was 1,130,530 and was divided among the three pilot groups as follows: Cargo (n = 361,519), Military (n = 56,547), and Passenger (n = 712,464).

Preprocessing

A web scraper was developed in Python 3.11.5, implementing the Beautiful Soup 4 library and standard built-in libraries (Richardson, 2023). Custom Cascading Style Sheets (CSS) selectors were written to retrieve links, posts, and timestamps. Posts from each subforum—Passenger, Cargo, and Military—were gathered into three data sets. Data were categorized as passenger, cargo, and military. Usernames were excluded to protect users' anonymity and eliminate excess data. The data were stored in JavaScript Object Notation format to be processed by the emotion analysis model later. The script was run from April 7, 2024 to April 8, 2024, to scrape all the acquired data.

NLP Model: $RoBERTa-base-go\_emotions$

$RoBERTa-base-go\_emotions$ (Lowe, 2023) is an NLP model trained from RoBERTa-base (Liu et al., 2019) on the $go\_emotions$ dataset (Demszky et al., 2020). The pretrained $RoBERTa-base$ model, created by FacebookAI, is derived from BERT (Devlin et al., 2018), though only uses the Masked Language Modeling (MLM) objective (Lowe, 2023). It is trained on a substantially larger English text corpus. Other key differences include training methodology and parameters for both NLP models. The GoEmotions dataset (Demszky et al., 2020), which $RoBERTa-base$ is trained on, consists of 58,000 Reddit labeled for 27 emotion categories or "neutral" (i.e., no emotion being expressed). This process generated the NLP $RoBERTa-base-go\_emotions$, which was implemented without fine-tuning via PyTorch and Compute Unified Device Architecture (CUDA) enabled to quickly analyze each of the posts (Lowe, 2023; PyTorch, 2024). The RobertaTokenizer from the Transformers library implemented a pre-trained tokenizer for $RoBERTa-base-go\_emotions$ (Lowe, 2023). The posts were processed with a max token length of 512, meaning each post was truncated to the first 512 tokens for processing. Each post was then given to the model, which returned a scoring for each of its 27 emotion categories and "neutral." The results were then stored as a comma-separated value file for statistical analysis.

Measures

Emotions

This study quantified and categorized emotions using the $RoBERTa$ emotions model, which detects 27 distinct emotions and "neutral" in text. The model provides confidence scores ranging from 0 to 1 for each emotional category, where 1 indicates high confidence in the emotion's presence, and 0 indicates low confidence. The 27 emotions identified by $RoBERTa$ are: admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, and surprise. The $RoBERTa$ model has demonstrated a strong ability to detect emotion (Imran, 2024) accurately.

Burnout

While this study investigated burnout as reflected in pilots' online discourse, the NLP approach operationalized this construct through emotional expression patterns associated with burnout rather than a comprehensive clinical burnout assessment. These burnout-related emotional indicators were measured using seven emotions associated

with burnout in prior literature: anger, annoyance, disappointment, disapproval, disgust, fear, and sadness. These seven emotions were averaged to calculate an exploratory composite score reflecting emotional aspects of burnout experience, which ranged from 0 to 1 and was consistent with the $RoBERTa$ emotion scores.

This approach represents a preliminary exploration of using emotional language as indicators of burnout-related experiences. While emotional expression cannot capture the full complexity of clinical burnout syndrome, prior research suggests that these specific emotions may serve as accessible linguistic markers of burnout-related distress in occupational contexts where traditional assessment faces barriers.

Our provisional and exploratory mapping of the four BAT facets to seven emotions to was as follows: (1) Exhaustion (disappointment, fear, sadness), (2) Mental Distance (anger, annoyance, disapproval, disgust), (3) Cognitive Impairment (fear), and (4) Emotional Impairment (anger, annoyance, disappointment, disgust, fear, and sadness).

Data Analysis

To address RQs 1 (levels of emotions) and 3 (burnout levels, as measured through emotional expression), descriptive statistics, including the mean and standard deviation, were calculated for all 27 emotions and the "neutral" category. To investigate RQ2 (differences in emotions and "neutral" across pilot categories) and RQ4 (differences in burnout levels across pilot categories, as measured through emotional expression), a one-way ANOVA was conducted, with the significance level (alpha) set at $p < 0.05$. For these inferential analyses, Cohen's f was reported as the effect size metric, with magnitudes interpreted according to Cohen's (1988) guidelines: 0.10 = small, 0.25 = medium, and 0.40 = large. Effect sizes below the 0.10 threshold (small effect) were considered practically equivalent, suggesting the absence of a meaningful effect based on the smallest effect size of interest (Lakens et al., 2018). For RQs 1-2, basic statistical analyses were performed using Microsoft Excel, while inferential analyses were conducted using the SciPy statistical package for Python (SciPy, 2024). For RQs 3-4, all statistical analyses, including creating the raincloud plot for RQ3, were performed using the R GUI JASP (JASP, 2024).

Results

This section reports the findings organized by research questions. First, we detailed the descriptive statistics for emotions and neutral across pilot types (RQ1), followed by group comparisons (RQ2). We then analyzed burnout scores as measured through emotional expression (RQ3) and group differences in these scores (RQ4).

Descriptive Statistics For Emotions And Neutral Across Pilot Types (RQ1)

RQ1 examined the levels of the 27 emotions and the "neutral" category (absence of emotion) identified by $RoBERTa$, using descriptive statistics. Across all pilot types, "neutral" was the most frequent category for cargo (M = 0.4473), passenger (M = 0.4667), and military (M = 0.4424) pilots. Among the 27 emotions, Curiosity (M = 0.1098) and Approval (M = 0.1062) were the most prevalent for cargo pilots. Approval was the most frequent emotion for both passengers (M = 0.11) and military pilots (M = 0.1231), while Curiosity was the second most common for both groups (M = 0.11 for passenger and M = 0.1231 for military). A complete list of the emotion levels, including means for each pilot group and for each emotion, is presented in Table 1 (see Appendix A).

Group Comparisons for Emotions and Neutral Across Pilot Types (RQ2)

RQ2 employed one-way ANOVAs to compare the three pilot groups (n = 1,130,530) across all 28 RoBERTa variables. The sample was distributed across pilot groups as follows: Cargo (n = 361,519), Military (n = 56,547), and Passenger (n = 712,464). Statistically significant differences were found for 27 of the 28 variables. The only variable that did not reach statistical significance was Surprise (p = 0.20). As shown in Table 1 (see Appendix A), the effect sizes (Cohen's f) for 26 of the 28 variables were below the threshold for a small effect ($f < 0.10$), with values ranging from 0.00 to 0.09. The effect sizes for the two remaining variables, Annoyance and Caring, were both f = 0.11, which is just above the threshold for a small effect size (Cohen, 1988). Figure 2 provides a comprehensive comparison between the three pilot groups (see Appendix A). The full data analysis results for the ANOVA can be found on this research project's website: https://osf.io/hgaz6/

Descriptive Statistics for Burnout Levels Across Pilot Types (RQ3)

To address RQ3, descriptive statistics were calculated for burnout scores (operationalized through emotional expression) across all pilot types (n = 1,130,530). Mean burnout scores and standard deviations were calculated for each pilot group: military (M = 0.018, SD = 0.029, n = 56,547), cargo (M = 0.020, SD = 0.032, n = 361,519), and passenger (M = 0.021, SD = 0.033, n = 712,464). The burnout score was derived from averaging seven emotions associated with burnout (anger, annoyance, disappointment, disapproval, disgust, fear, and

sadness). As shown in Table 1 (see Appendix A), these component emotions consistently showed low mean values across all pilot groups, with individual emotion means ranging from 0.0029 to 0.0579. The relative contribution of each emotion to the overall burnout score can be observed in Figure 2 (see Appendix A), where disapproval showed the highest mean values (Cargo: $M = 0.0536$; Military: $M = 0.0462$; Passenger: $M = 0.0579$) among the burnout-related emotions.

Difference for Burnout Levels Across Pilot Types (RQ4)

RQ4 employed a one-way ANOVA to compare burnout levels across the three pilot types. The ANOVA revealed a statistically significant difference, $F(2, 1{,}130{,}527) = 437.66$, $p < .001$, Cohen's $f = 0.028$. This small effect size suggests that the difference in burnout scores between pilot groups, while statistically significant, is not practically meaningful. This finding aligns with the results for RQ2, further supporting the assertion of practical equivalence between the pilot groups regarding burnout. The raincloud plot visually represents this practical equivalence (see Figure 3, Appendix A), which displays the distribution of burnout scores for each pilot type. The raincloud plot combines raw data points, a half-violin plot showing the probability density, and a box plot with summary statistics. Visual inspection of Figure 3 reveals minimal separation between the distributions of the pilot types, indicating that the differences in burnout scores are not practically meaningful. The pilot groups exhibit very similar distributions, further supporting the argument for practical equivalence (see Figure 3, Appendix A).

Discussion

The present study was designed to investigate emotions associated with burnout in commercial, cargo, and military pilots by examining pilots' online discourse within forum posts. While our approach provides preliminary insights into emotional aspects of burnout through linguistic analysis, it represents an exploratory method that complements, rather than replaces, established burnout assessment approaches. RQ1 examined the levels of emotions expressed in pilots' online discourse. RQ2 was a comparative analysis of the emotions expressed in passenger, cargo, and military pilots' online discourse. RQ3 identified the level of burnout reflected in the language of pilots' online discourse, as measured through emotional expression patterns. RQ4 determined whether the level of burnout reflected in pilots' online discourse differed based on the pilot category, as measured through emotional expression patterns. The analysis revealed that language associated with typical burnout-related emotions in pilots' online discussions was less prevalent than positive emotions. Furthermore, linguistic patterns reflecting emotions show more similarities than differences across passenger, cargo, and military pilot categories. Following an analysis of the results of each research question, subsequent sections note study limitations and implications.

RQ1 investigated the most common emotions conveyed in the online discussion of pilots. Across all three pilot categories, "neutral" emerged as the predominant emotional tone, followed by expressions of curiosity and approval. One explanation for this finding was that the training of pilots was designed to handle critical incidents with controlled emotional expression (Lu et al., 2023; Nergård & Svendsen, 2016). Beltran (2024) explored the absence of self-awareness training in aviation training, positing that cultural bias, difficulty in operationalizing the construct, lack of training in identifying emotions and self-awareness in existing aviation trainers, and a collective sense of non-importance within the profession explained this deficit. A second possibility was that the presence of neutrality, or the absence of emotions, may have indicated emotional suppression associated with burnout experiences. While pilot training may contribute to a neutral communication style, the pervasiveness of neutrality across different pilot categories, coupled with the established literature on pilot burnout (Brezonakova, 2017; Cullen et al., 2021; Tsismalidou & Kondilis, 2024) suggested that repressed burnout is a more likely explanation. This interpretation was further strengthened by recent research focused on the inability to feel as a component of burnout. A large body of literature indicated that gradual emotional depletion or emotional exhaustion strongly indicated burnout (Demerouti, 2015; Freudenberger, 1975; Maslach & Jackson, 1981; Maslach et al., 1996). More recent research has examined job-related factors and their connection to the inability to feel as part of the definition of burnout (Tavella et al., 2020).

Given the diverse operational environments of the pilot groups assessed, the RQ2 results differed from what might have been expected. The analysis indicated more similarities than differences in the language these distinct pilot categories use. There were subtle variations observed, such as higher levels of admiration and gratitude among military pilots, elevated levels of amusement and anger in passenger pilots, and minimally higher levels of curiosity among cargo pilots. However, the emotions observed were primarily homogenous. There are several possibilities for the overall similarity in emotion expression across groups. First, it could have indicated the standardized nature of pilot training and professional conduct, regardless of the specific aviation sector. A second possibility could have been gendered speech patterns. According to the FAA civil airmen statistics, aviation continues to be male dominated, with around 90% of pilots being male and 10% female (FAA, 2023a). A third reason is that all pilots, regardless of sector, face fundamentally similar

occupational demands and regulatory environments. Of the three possibilities, the third is the most likely reason. The similarity between the three pilot subsectors likely stems from shared occupational stressors, expressed in their language, that transcended specific pilot categories. All pilots face common challenges including safety responsibilities, regulatory oversight, irregular schedules, and high-stakes decision making environments (Demerouti et al., 2019; Fanjoy et al., 2010). These universal aspects of pilot work may create similar emotional responses and discussion topics regardless of whether pilots fly passenger, cargo, or military aircraft. This explanation is supported by the Sapir-Whorf hypothesis, also known as linguistic relativity, which specifies that the structure and content of language are impacted by culture and the shared lived experiences of individuals and groups (Baxriddinov, 2024). As such, aviation culture and its linguistic patterns have the potential to influence worldviews and shape the expression of emotion, as reflected in the online posts examined.

The RQ3 analysis revealed that these burnout-associated emotions were expressed at lower levels than more positive emotions within the examined online conversations. It is crucial to note that the relative absence of these emotions in online discourse does not necessarily indicate an absence of burnout itself; rather, it may reflect how burnout is expressed or managed within this specific professional context. The findings suggested several possibilities. First, pilots, as a professional group, may be generally resilient and maintain a positive outlook despite the challenges inherent in their occupation. A second potential is that it could reflect a professional culture that discourages the open expression of negative emotions, particularly in public forums. A third possibility is that the lower prevalence of burnout-related emotions might also be attributed to effective stress management techniques or support systems within the aviation industry. The most likely explanation is that aviation professional culture, through establishing policies that impact one's ability to hold a pilot's license, has dissuaded pilots from freely expressing emotions. For example, according to federal regulations, pilots must participate in routine health evaluations and disclose any emerging or intensifying physical or mental health issues to retain their flying privileges (14 C.F.R. § 67.10, 2023). It is important to note that recent FAA developments could positively influence the culture of non-reporting mental health concerns due to the permissibility of certain diagnoses or conditions (FAA, 2024).

Regarding RQ4, while there was a statistically significant difference, the low effect size meant the differences did not have practical significance. The first possible explanation for this finding may relate to the universal characteristics of the broader pilot profession. Despite operational differences between passenger, cargo, and military contexts, the essential job requirements remained consistent across all pilot categories. Inherent job demands like1 maintaining situational awareness, making time critical decisions under pressure, and oversight and responsibility for aircraft safety (Demerouti et al., 2019; Fanjoy et al., 2010) may have produced similar emotional responses regardless of the specific aviation sector. An alternative explanation for this finding may be due to the reporting culture of the aviation profession. Pilots across all categories may have exhibited similar behaviors when it came to disclosing mental health issues. The fear of losing flight status due to reporting such issues can motivate pilots to withhold or misrepresent their mental health status (Hoffman et al., 2023). This culture of nondisclosure or underreporting may result in a homogenous presentation of burnout levels across different pilot groups. Between the former and latter, the aviation profession's self-reporting culture is the most likely explanation for the nonsignificant differences in burnout levels between passenger, cargo, and military pilots. The stigma associated with mental health issues in the aviation industry might have discouraged pilots from self-reporting burnout (FAA, 2023b). Second, the fear of repercussions and potential consequences of self-reporting burnout may have strongly motivated pilots' self-reporting behaviors. These concerns likely reflect the aviation industry's overall culture and influence the self-reporting behaviors in all pilot groups.

Limitations

While the findings in this study have value in better understanding the phenomenon of burnout in aviators based on the online discourse contained in the referenced forum, some important limitations must be considered. First, our mapping of NLP produced levels of specific emotions to latent aspects of a complex psychosocial, social, and physical phenomenon should be viewed as exploratory and provisional aimed at suggesting future avenues of research on pilot burnout. While $RoBERTa$, the NLP model chosen for this study, exceled at identifying emotional tone in text, its capacity to capture the full multidimensionality of burnout remained inherently limited. In addition to emotional experience, burnout encompasses cognitive, behavioral, and physiological components.

Second, our selection of seven emotions to represent aspects of burnout, while grounded in literature, represented only a subset of emotions associated with burnout experiences. We acknowledge that our approach does not directly capture core burnout symptoms such as exhaustion and fatigue, which are prominent in established frameworks (Maslach & Jackson, 1981; Schaufeli & De Witte, 2023; World Health Organization, 2019). Notably absent from our analysis were direct linguistic markers of these core burnout dimensions, as well as cognitive impairment and reduced professional efficacy.

Third, the forum from which the data points were gathered did not require verification that contributors were or had worked as pilots, thus creating the possibility that some of the data points may have been reflective of contributors who represented their perceptions or biases about the experiences of pilots. Additionally, the forum did not differentiate between contributors who have active flight status, aspiring pilots, and those who were retired or grounded, thus creating an opening for bias that could have represented the perspectives of aviators who are no longer flying for various reasons, or who had never flown. Finally, the viewpoints expressed in the selected forums represented the views of those who chose to post, omitting an unknown number and variety of additional viewpoints from other aviators. As a separate consideration, it was worth noting the impact that anonymity and group identification may have had on the online posting behaviors of forum contributors. Anonymity has been discussed among several factors that could impact user behavior in online forums (Suler, 2005). Thus, anonymity in the chosen forum may have contributed to some respondents expressing their experiences in ways they would not have with an identifiable profile, thus potentially skewing the representation of burnout-related language in the body of text analyzed. Similarly, Gaulan et al. (Gaulan et al., 2025) described their investigation of shame in the context of an Israeli peer advice forum. Their findings highlighted how culture could influence the degree of vulnerability participants were willing to express in online forums, regardless of anonymity. Given the speculations made by authors such as Beltran (Beltran, 2024) regarding attitudes about emotion and self-awareness in aviation culture, we may have been able to extrapolate a potential impact on the content of the forums we examined.

Implications

Based on the results and limitations of this study, three recommendations could be made for future research on this topic. First, future research should validate these preliminary emotional indicators against established clinical burnout measures to determine the relationship between linguistic expression and clinical symptomology. Longitudinal studies comparing NLP-derived emotional patterns with standardized burnout inventories (e.g., Maslach Burnout Inventory, BAT) could establish the validity of emotional language analysis in occupational health screening. Further research might also explore whether online emotional expression accurately reflects pilots' lived experiences or whether there were discrepancies between public discourse and private realities. It is important to note that while neutrality was not explicitly examined as an emotion related to burnout in this study, the findings warranted further investigation. Future research should explore the relationship between neutral emotional expression and clinically assessed burnout, specifically within aviation, to provide more definitive conclusions.

Second, while substance misuse among pilots has been examined in recent comprehensive reports (National Academies of Sciences, Engineering, and Medicine, 2023), future studies should specifically investigate the relationship between emotional expression patterns identified through NLP analysis and substance misuse behaviors. Such research could determine whether linguistic markers associated with burnout correlate with substance misuse as a coping mechanism, potentially providing early warning indicators.

Third, longitudinal studies that tracked pilots' mental health over time can offer a deeper understanding of how burnout develops and progresses, enabling the identification of critical intervention points and the assessment of the long-term effectiveness of support programs. Three implications for future practice can be drawn from the obtained results. First, it is essential to develop and implement customized mental health support programs that address the unique stressors faced by each type of pilot. Since "neutral" and positive emotions were most prevalent in the online discourse, pilots might be suppressing negative emotions or benefiting from resilience training. Second, current or former pilots can benefit from engagement in online forums with other pilots. The large corpora gathered from these forums indicates that this space benefits this population. Third, the FAA can benefit from campaigns or wellness initiatives that support employees' mental health. An important observation is that there were hundreds of thousands of posts across pilot groups, yet no identifying pilot information is required to engage with other pilots. This anonymity of pilots may indicate a need not otherwise supported by the airline industry.

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Appendix A

Table 1

RoBERTa 27 Emotions and Neutral in Rank Order by Average of the Means (RQs 1–2)

	Mean					
Variable	**Cargo**	**Military**	**Passenger**	***F***	***Cohen's f***	**ES Magnitude**
neutral	0.4473	0.4424	0.4667	157.38	0.06	Trivial
approval	0.1062	0.1231	0.1100	247.96	0.07	Trivial
curiosity	0.1098	0.1006	0.1037	132.89	0.03	Trivial
confusion	0.0801	0.0714	0.0768	108.89	0.04	Trivial
gratitude	0.0600	0.0681	0.0441	703.06	0.08	Trivial
admiration	0.0457	0.0581	0.0438	256.90	0.07	Trivial
optimism	0.0474	0.0530	0.0485	39.72	0.03	Trivial
disapproval	0.0536	0.0462	0.0579	343.36	0.07	Trivial
realization	0.0269	0.0309	0.0275	134.76	0.05	Trivial
caring	0.0187	0.0286	0.0166	682.48	0.11	Small
annoyance	0.0324	0.0255	0.0363	689.37	0.11	Small
disappointment	0.0249	0.0250	0.0260	27.87	0.01	Trivial
joy	0.0175	0.0210	0.0177	50.01	0.03	Trivial
amusement	0.0200	0.0199	0.0268	399.48	0.05	Trivial
sadness	0.0126	0.0148	0.0114	107.04	0.04	Trivial
desire	0.0098	0.0118	0.0100	47.29	0.03	Trivial
surprise	0.0117	0.0115	0.0119	1.62	0.00	Trivial
remorse	0.0105	0.0109	0.0087	98.84	0.02	Trivial
love	0.0081	0.0096	0.0084	15.92	0.02	Trivial
excitement	0.0097	0.0093	0.0102	26.22	0.02	Trivial
anger	0.0064	0.0045	0.0072	198.30	0.06	Trivial
fear	0.0034	0.0039	0.0036	8.83	0.01	Trivial
relief	0.0027	0.0037	0.0027	373.58	0.09	Trivial
disgust	0.0034	0.0029	0.0041	133.26	0.04	Trivial
embarrassment	0.0027	0.0025	0.0030	29.54	0.02	Trivial
nervousness	0.0022	0.0019	0.0019	16.28	0.02	Trivial
pride	0.0013	0.0017	0.0013	123.03	0.05	Trivial
grief	0.0008	0.0010	0.0008	493.01	0.08	Trivial

Figure 1

Study Methodology Flowchart Showing Data Collection, Processing, and Analysis Pipeline

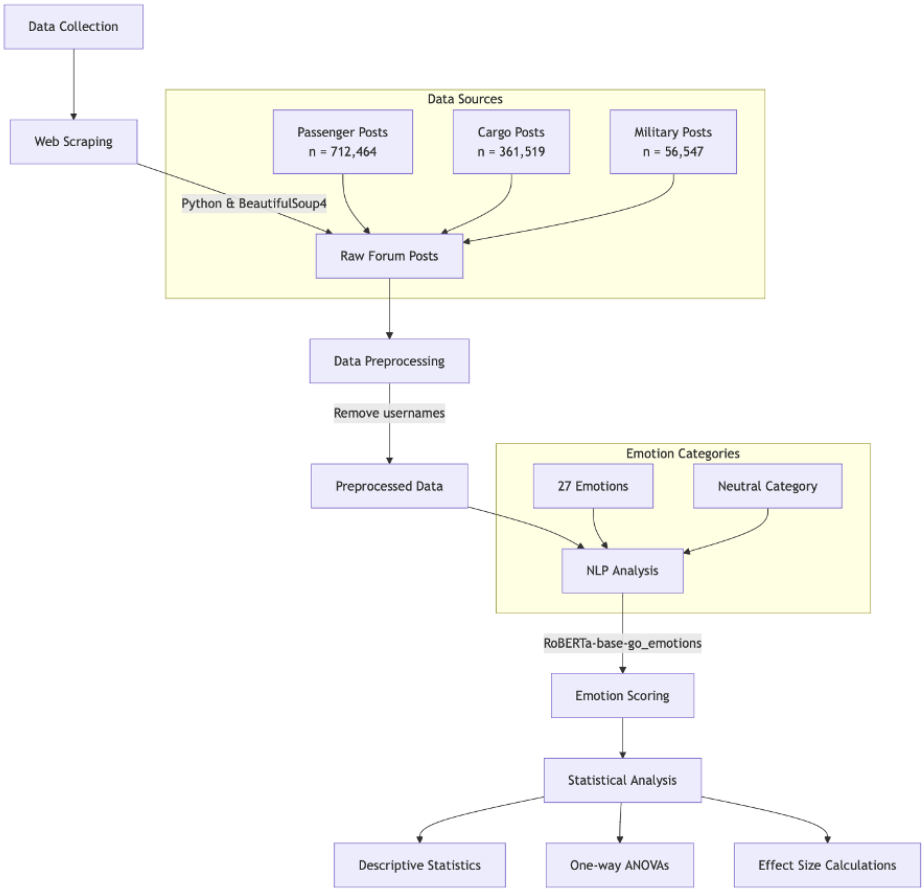


Figure 2

Distribution and Magnitude of Emotional Expression in Aviation Pilot Forum Posts (RQ2)

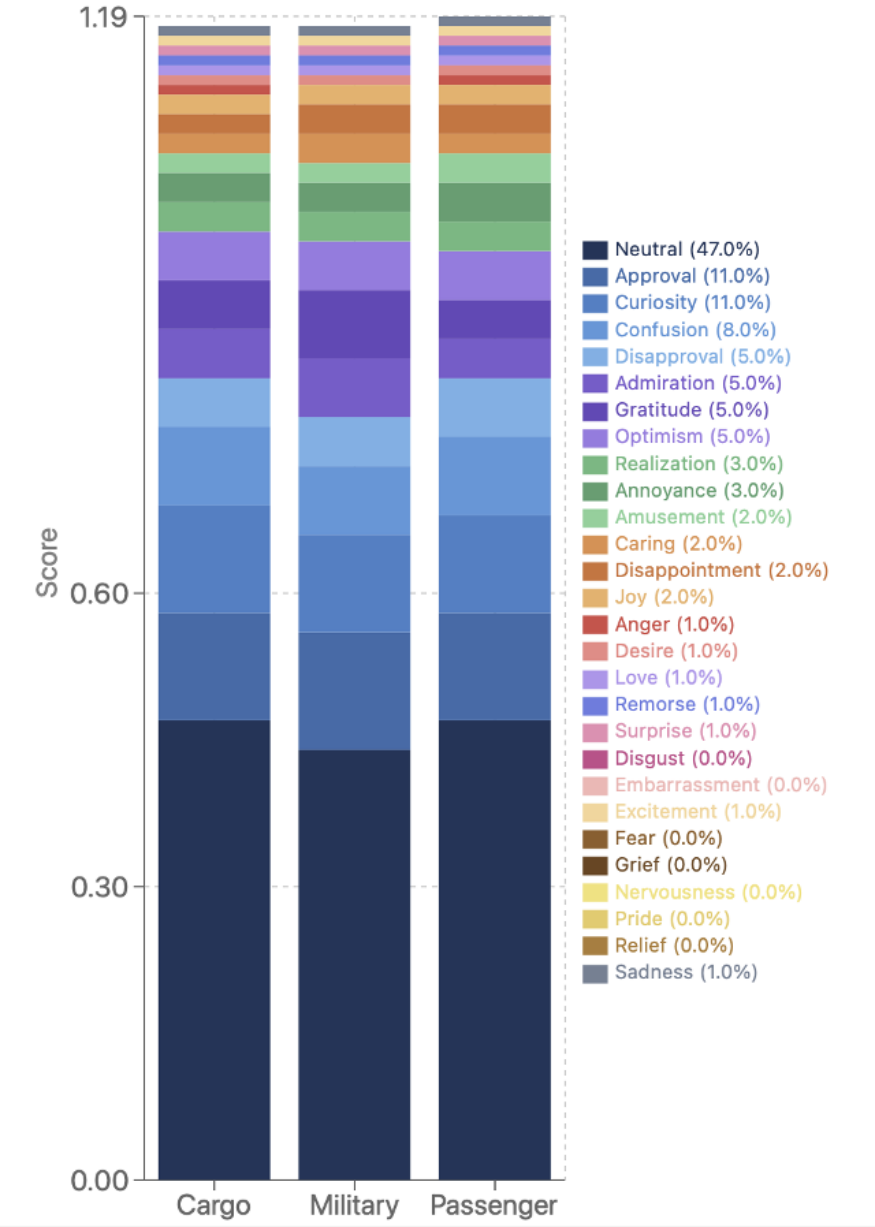
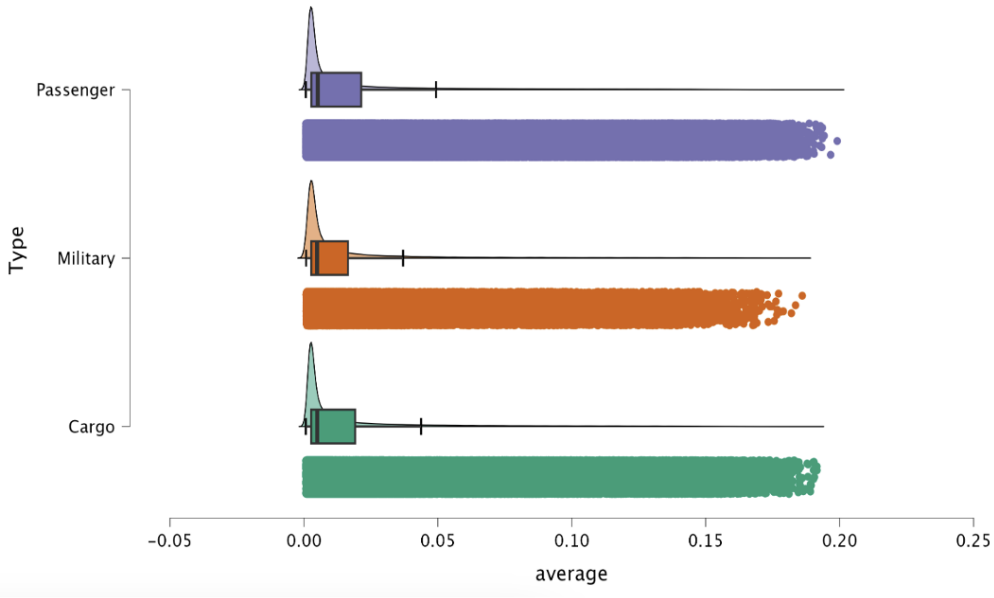


Figure 3

Comparison of Burnout Levels Amongst Pilot Types (RQ4)



Appendix B

Human Subjects Review Statement

This study was deemed exempt from review by the University of Nevada, Reno Institutional Review Board (IRB 2174745-2, March 29, 2024) under Exemption Category #4(i) in accordance with the Code of Federal Regulations on the Protection of Human Subjects (45 CFR 46.104).

1. Revising the research questions
2. Writing the abstract
3. Operationalizing burnout
4. Brainstorming discussion and implications for future research and practice
5. Improving sentence structure and minimal paraphrasing
6. Reorganization of methodology section while retaining all original narrative written by authors
7. Generation of study methodology flowchart
8. Brainstorming headers for results section
9. Writing of first paragraph in results section
10. Brainstorming about the provisional and exploratory nature of our NLP to BAT facet mapping
11. Comparing manuscript edits made by authors with those requested by peer reviewers to assess whether sufficient changes were implemented

All prompt engineering input and LLM output done in conjunction with this study can be reviewed on the project's website: https://osf.io/hgaz6/

Appendix C

Author Declarations

Authors' GenAI Usage Statement

In conformity with the World Association of Medical Editors (2023) standards on the use of LLMs with academic writing, the authors report the following use of LLMs regarding the planning , execution, and reporting of the research contained in this manuscript:

Appendix D

CRediT Author Statement

Adrienne S. Renwick: Conceptualization, Writing- Original draft preparation, Writing- Review and Editing, Visualization, Project administration. **Leo Gonzalez:** Conceptualization, Writing- Original draft preparation. **Charles L. Silber:** Formal analysis, Writing - Original draft preparation. **Alyson Mullen:** Conceptualization, Writing- Original draft preparation, Visualization. **Cass Dykeman:** Methodology, Writing- Review and Editing. **Adam Stewart:** Software, Data Curation, Writing- Original draft preparation. **Jennifer C. Ross:** Writing- Original draft preparation, Writing- Review and Editing. **James Geisler:** Conceptualization, Writing- Original draft preparation.

Funding Statement

No author has any funding declarations.

Data Availability Statement

The following are available on this research project's website (https://osf.io/hgaz6/): (1) FAA Civil Airmen 2023 Statistics, (2) G*Power sample, (3) generative AI use logs, (4) IRB proposal 2174745-2 Exempt Determination, (5) raw data, (6) ANOVA statistical analyses, and (7) tables and figures.

Conflicts of Interest Statement

No author has any conflicts of interest declarations.