

Expert Performance and Time Pressure: Implications for Automation Failures in Aviation

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Abstract. Human-automation interaction has become one of the most important issues in aviation safety. Although automation generally increases air travel safety and efficiency, sudden automation failures have produced tragic results. Automation failure can require a previously disengaged human pilot to react immediately to counter a dangerous situation. In other words, automation failure can inflict time pressure on human expertise. Studies of expert performance have disagreed on how resistant it is to time pressure effects. This study examined time pressure effects on some of the most expert chess players in the world. The results show that time pressure can have profound effects even on extremely high-level expert performance. Implications for the aviation domain are discussed.

Keywords: Expertise, Time Pressure, Automation

Introduction

Human-automation interaction has been a challenge for human factors for quite some time and its relevance continues to grow (e.g., Bainbridge, 1983; de Winter & Dodou, 2014; Fitts, 1951; Jordan, 1963; Parasuraman & Byrne, 2003, Sheridan & Parasuraman, 2005; Welford, 1958). Among the challenges, automation failures can produce sudden and critical moments in which human expert performance is subjected to severe testing. Consider two examples below.

Example One – On July 20, 1969, the first manned spacecraft to attempt a landing on the moon, the *Eagle*, approached the lunar surface. Much of the approach sequence was under the automated control of a computer. Suddenly a computer flashed a light to indicate a “Program Alarm” and its display froze with an error code displayed. In the *Eagle* Neil Armstrong and Buzz Aldrin began troubleshooting the problem, as did Michael Collins in the Apollo Command Module and many people in Houston Control. As Buzz Aldrin recalled it was a tense moment, “Back in Houston, not to mention on board the *Eagle*, hearts shot up into our throats while we waited to learn what would happen” (Collins & Aldrin, 1975, p. 212). Neil Armstrong tested flight controls to determine if they were still working. Throughout all of this troubleshooting, both astronauts had their attention inside the vehicle. At about 2,000 feet Armstrong looked out the window and realized that the descent trajectory was aimed at a crater surrounded by boulders. With an error code still showing on the display Armstrong took control away from the computer and guided the *Eagle* to a safe landing area. At touchdown, only 40 to 50 seconds of fuel remained. In this case, the human was able to compensate for the sudden automation alarms and successfully complete the historic mission (Mindell, 2011).

Example Two – On June 1, 2009 Air France (AF) Flight 447 was heading out of Rio de Janeiro to cross the Atlantic Ocean and land in Paris. Unfortunately, multiple large storm systems were in their path. Flying into the storms caused the three pitot tubes that provided airspeed information to the automated flight control system as well as to the cockpit displays to freeze-up. The resulting lack of airspeed information caused the autopilot to disconnect; which meant the human crew had to take over. This was a sudden, challenging, and dangerous situation, but according to France’s Bureau d’Enquêtes et d’Analyses pour la sécurité de l’aviation civile (2012), it should have been handled by the flight crew. However, in this event, “The crew, progressively becoming de-structured, likely never understood that it was faced with a ‘simple’ loss of three sources of airspeed information” (Bureau d’Enquêtes et d’Analyses pour la sécurité de l’aviation civile, 2012, p. 199). During the confusion the Pilot Flying’s control inputs induced a stall which caused the big airliner to lose all lift and to ultimately plunge from a flying altitude of approximately 35,000 feet into the ocean. The time from the autopilot disconnecting to the crash was approximately 4 minutes and 23 seconds. The accident caused 228 fatalities, including the crew.

The two examples differ dramatically in terms of their outcomes and the systems involved, but they are both examples of an important trend in aerospace systems. More and more, the human is interacting with automated systems that generally do a good job, but sometimes will fail suddenly at unexpected moments during critical situations. In such rare moments it is up to the human step in and take control. At these points the human’s expertise must cope with the time pressure imposed by having to act quickly to produce the correct input, or at least to avoid an incorrect act (Sherry & Mauro, 2015). In these time critical moments, the human must perform an immediate, or at least very quick, situation assessment that leads to the correct actions.

But, how well do human decision makers, even highly expert human decision makers, deal with such time pressure? This is not an easy question to address in typical laboratory research because true experts in any domain, including perhaps especially aviation, are often difficult to recruit for laboratory research and realistic tasks that would invoke their expertise often require sophisticated and expensive simulators. To circumvent these difficulties, the current study examines the effect of time pressure on the performance of world-class experts in chess. Specifically, the performance of chess grandmasters competing in real chess tournaments inflicting very different levels of time pressure was examined.

An immediate and fair question regarding the present experiment might be, “But, what does chess playing have to do with automation in aviation?” It is a fair question because the two domains are, after all, very different. However, in terms of the cognitive processes assumed to be involved there is more similarity than might be immediately obvious. For example, both domains involve lengthy training to develop perceptual abilities to recognize opportunities or dangers. Both aviation and chess also require the cognitive flexibility to update or revise a plan when circumstances change. And, both aviation and chess will sometimes force the expert to act when there is very little time available to think. So, chess is a reasonable domain for studying expert performance with the expectation that the results will generalize to other domains, including aviation.

Furthermore, chess has several important advantages as an especially attractive domain for examining time-pressure effects on highly expert performance: (1) an established rating system for evaluating player expertise, (2) competitions conducted under varying time

constraints, and (3) sophisticated chess evaluation software for detailed move-by-move performance analysis.

Chess Expertise Rating System. Competitive chess players are carefully ranked by national chess associations and the Fédération Internationale des Échecs (FIDE) via the Elo ranking system (Elo, 1978, Glickman, 1995, Howard, 2006). Under the Elo system a beginner is expected to have a ranking of approximately 600 to 800 Elo points. Anyone possessing over 2000 points would generally be considered an expert (Vaci, Gula, & Bilalić, 2014). At the highest end of the chess expertise scale, grandmasters would have ratings above 2500 points. Points are earned by defeating or drawing against higher-rated players in sanctioned events, or lost by losing or drawing against lower-rated players. Elo ratings have been successfully used to gauge expertise in previous studies of expertise (e.g., Calderwood, Klein, and Crandall, 1988; Chabris and Hearst, 2003; Howard, 2006).

Chess Time Constraints. Time allotments to the two players is one of the key variables defining different competitive events. Each player has his/her own clock that counts down whenever it is their move. If a player's cumulative elapsed time exceeds their allotted time, then they lose the game. For many years, the standard time allotment for each player in major events was two and a half hours for the first 40 moves with an additional allotment of one hour for every 16 moves thereafter. As mechanical chess clocks were supplanted by computerised digital clocks, the time allotments now often include additional time allotments with each move made (typically 10 to 30 additional seconds per move). Also, although major events will usually specify something akin to the standard time allotment with additional time per move allotments, some events will induce more time pressure on the competitors by allowing only 15 minutes (typically referred to as Rapid events), or even only 5 minutes (typically referred to as Blitz events), for the entire game.

Chess Evaluation Software. Chess game-playing and analysis software operates by using algorithms to perform a positional analysis of the current position, and then similar analysis of all legal moves can identify the best possible move according to the algorithms. When analysing a move made by a human player, the software operates by subtracting the evaluation of the player's actual move from the evaluation of the best possible move according to the algorithm and produces a calculated blunder size of any move made other than the best possible. During the last decade or so there has been an emerging consensus that such computer evaluation of chess moves enables in-depth and unbiased evaluation of chess positions and moves (Chabris & Hearst, 2003). As Garry Kasparov, the former Chess World Champion (1985-1993), described computerized chess, "Your pocket calculator has no trouble calculating 89×97 , and chess programs like Fritz and Junior are just as quick to produce the solutions to complicated tactical positions. The trawl through all the possibilities looking for the path that leaves them with the most material. It's a brute force system that isn't particularly elegant, but in complex positions it's undeniably effective." (Kasparov, 2007, p. 58). Furthermore, Computer-aided training has been credited for improving the chess play of modern champions versus earlier champions (Breutigam, Yusupov, & Lutz, 2004). It has also become common to evaluate performance in chess championship play by comparing the chess moves made to computer recommendations during the match (e.g., Topalov & Ginchev, 2007). As K. Anders Ericsson (2014, p. 459) put it, "Today's chess programs are so much better than human players that their selected move can be used as a gold standard for the best move."

The effects of time pressure has been examined in chess performance before, but the results have been mixed. For example, Calderwood et al., (1988) compared the rated move quality

for three Class B (average Elo rating = 1750) and three Master level (average Elo rating = 2435) chess players playing under either standard time constraints or blitz chess (5 minutes allowed for each player). The move quality for each move in the games (other than the opening moves) were then rated on a 5-point scale by a grandmaster blinded to the expertise level of the player making the move and the type of event that the game came from. Although the move quality ratings were significantly higher for the moves made by the Master level players, no difference was detected between the standard and blitz time controls. However, Chabris and Hearst (2003) used computerized chess analysis to compare grandmasters playing either standard time control games or rapid time controls (approximately 25-30 minutes allowed for each player). Their results showed that rapid chess led to more and larger blunders. So, Calderwood et al. (1988) found no time pressure effect in lower-rated chess players confronted by higher time pressure than used in the Charis and Hearst (2003) research that did find a time pressure effect.

The different findings of the Calderwood et al. and the Chabris and Hearst experiments could potentially have resulted from differences in their experimental designs and procedures. For example, Calderwood et al. had only three players in each of their two groups and each player's data came from a total of eight games. This suggests that statistical power might have been quite limited, despite the fact that the results found a statistically significant difference in move quality due to skill level (i.e., Master players versus Class-B players). In contrast, Chabris and Hearst studied the performance of 23 grandmasters in hundreds of games. Another possibility for the disparity in outcomes could be that the computerized brute force assessment used by Chabris and Hearst, might have produced a more thorough tactical evaluation than the subjective expert ratings used in the Calderwood et al. research. Calderwood et al. (1988, pp. 486-487) themselves suggested that limited sensitivity might have been a contributor to the failure to detect a difference between standard and blitz play: "The possibility of exists that our rating scale was not sensitive enough to reflect decrements in move quality under blitz conditions, although the fact that the scale did detect differences in player strength somewhat belies this explanation."

Whatever the explanation for the differences in the results, the effect of time pressure on expert chess performance was not settled by these two studies. To help resolve the disagreement between the previous research findings, the present work used a computerized chess move analysis procedure to examine top-level grandmaster chess performance in standard time control chess versus blitz chess.

The current experiment was explicitly designed to address two questions:

1. Would players at the highest levels of expertise be susceptible to time pressure effects?
2. Would the degree of time pressure effect be associated with the level of expertise of the individual grandmasters?

If such highly-rated chess players were more likely to blunder under time pressure, it would suggest that even a skilled human pilot suddenly confronted with time pressure due to an automation failure could also be vulnerable to performance degradation.

Method

Data Source

One of the most prestigious annual chess tournaments is held in the Dutch city of Wijk aan Zee. It is a standard time control tournament that attracts many of the top-rated players in the world. In 1999, the standard time control tournament was supplemented by a blitz tournament. Although not all competitors from the standard time control tournament competed in the blitz tournament, 13 players did. The experimental data set was created by downloading games from the tournament website. All available games for both events were analysed with the Fritz 9 chess software (Morsch, 2005). The Fritz software identified blunders by calculating positional evaluations resulting from all possible moves that could be made; if the move that the player selected was not the best, then the difference between that move's positional evaluation and the best possible positional evaluation would be the blunder size. Any pairing of participants that had missing data or failed to have at least one Fritz-evaluated move for both players in the same event were deleted from the present analysis. Thus, for any given player the performance in either event was based on games against identical sets of opponents. Ultimately, 58 game pairs (with each game providing data for two players) were identified and provided the data for the players' performance in the two events.

Participants

Thirteen grandmaster chess players that participated in the 1999 Wijk aan Zee chess tournament provided the data for this study (see Table 1). Their mean Elo Rating was 2670 (95% Confidence Interval (CI), [2620, 2719]). The range of ratings was from 2540 to 2812. Six of the grandmasters were ranked in the top ten in the world according to the most recent FIDE rankings (British Chess Magazine, January, 1999). The then-current World Chess Champion (i.e., Garry Kasparov) was among the top players that competed in the tournament.

Table 1. Player Elo ratings

Player #	Player Name	Elo Rating
01	A. Yermolinsky	2597
02	D. Reinderman	2540
03	G. Kasparov*	2812
04	I. Sokolov	2610
05	J. Piket	2609
06	J. Timman	2649
07	L. van Wely	2636
08	P. Svidler*	2713
09	R. Kasimdzhanov	2595
10	V. Anand*	2780
11	V. Ivanchuk*	2714
12	V. Kramnik*	2751
13	V. Topalov*	2700

* = Ranked in the Top-10 FIDE Ratings (British Chess Magazine, 1999)

Initial Data Processing

All games from the standard tournament and the blitz tournament were analysed by the Fritz chess software. The software analysed any move that it did not recognize as part of an identifiable opening sequence or that did not have a possible forced mating sequence. For any evaluated move the value of the resulting position would be calculated; a zero positional evaluation indicated an even game, positive values indicated an advantage for the white player, and negative value indicated an advantage for the black player. To identify any

blunder, the Fritz software also calculated any difference between the positional value of the move played and the value of the best possible move according to its calculations.

Calculation of Each Player's Expected Blunder per Move (EBPM) scores

Following the Initial Data Processing step, the blunder evaluations for each player were summed for each event and divided by the total number of evaluated moves to create the Expected Blunder per Move (EBPM) score. Table 2 shows the number of analysed moves each player made in each event and their mean EBPM score for each event.

Table 2. Player Data by Time Control Event Type

Player #	Player Name	Standard Games # of Moves	Standard Games EBPM	Blitz Games # of Moves	Blitz Games EBPM
01	A. Yermolinsky	243	0.0878	274	0.3364
02	D. Reinderman	288	0.3466	292	0.4786
03	G. Kasparov	180	0.1076	292	0.2704
04	I. Sokolov	164	0.0821	327	0.4544
05	J. Piket	154	0.1794	359	0.5358
06	J. Timman	257	0.1721	264	0.4066
07	L. van Wely	156	0.1564	257	0.3936
08	P. Svidler	125	0.3718	282	0.4570
09	R. Kasimdzhanov	194	0.2648	203	0.7502
10	V. Anand	106	0.1745	186	0.2585
11	V. Ivanchuk	182	0.1186	240	0.2158
12	V. Kramnik	95	0.0807	180	0.2797
13	V. Topalov	255	0.1945	339	0.4454

Notes. All blunders were converted to absolute values to allow the combination of blunders whether playing the White or Black pieces.

Results

Event Type Effect on EBPM

To test whether the increased time-pressure exerted by the Blitz event actually degraded the grandmasters' performance, a *t*-test was calculated to compare the players' performance in standard time control games to their Blitz game performance. The *t*-test found a significant effect of Tournament Event Type on the EBPM measure ($t_{(12)} = 6.723$, $p < 0.0001$, $d = 1.865$). As listed in Table 3 and illustrated in Figure 1, the average EBPM in the Blitz event was substantially higher than in the Standard tournament event. As a rule of thumb Cohen (1988) suggested that any effect size larger than 0.8 could be considered a large effect.

Table 3. Mean EBPM, Standard Error, and 95% Confidence Intervals by Event Type

Event Type	Mean EBPM	Std. Error	95% CI
Standard	0.180	0.026	[0.122, 0.238]
Blitz	0.406	0.040	[0.320, 0.492]

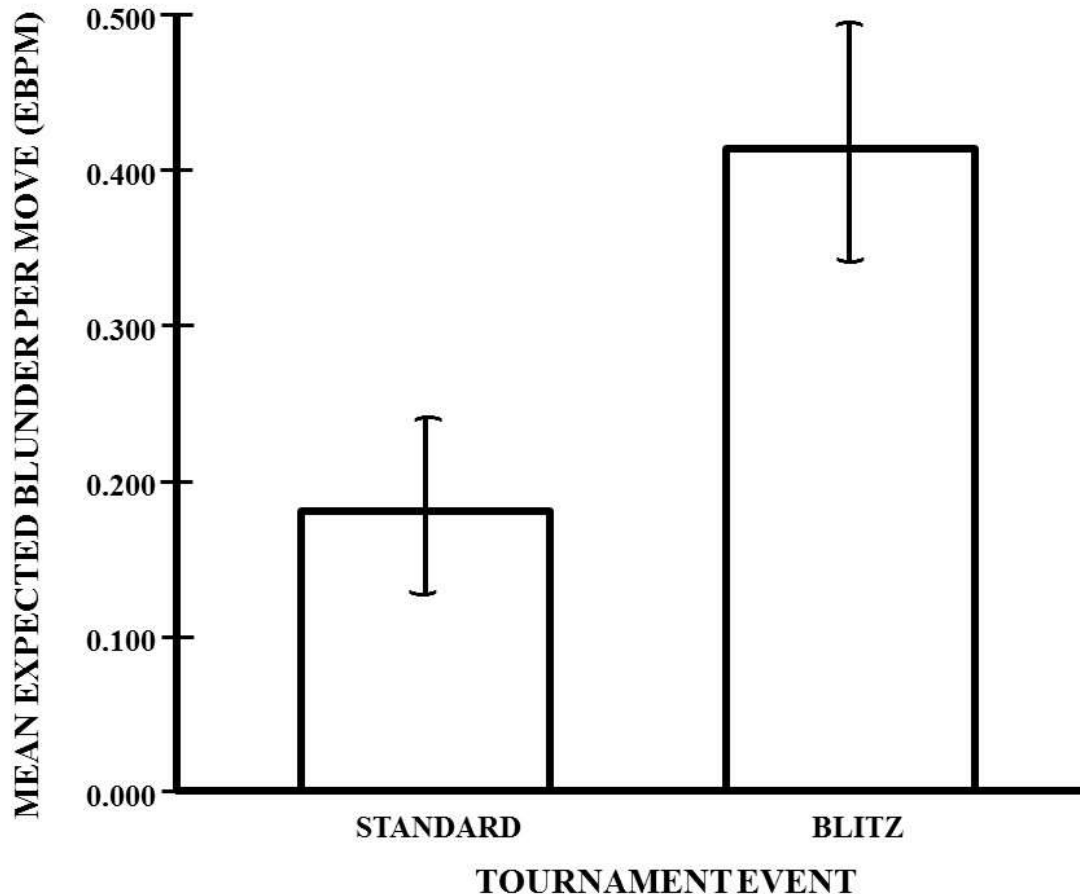


Figure 1. Mean EBPM (and 95% CIs) as a function of Tournament Event type.

Elo-EBPM Correlation Analysis

Although the above analysis shows that the group, as a whole, was degraded by time pressure, it does not explore whether the higher-rated players within this highly-selected group were more resistant to time pressure than the lower-rated players. To test whether the different levels of expertise across the players influenced their performance in the two events, correlations between the players’ Elo ratings and their mean EBPM performance in each of the tournament events were calculated.

Interestingly, the correlation was not significant for the Standard tournament event analysis ($r_{(11)} = -0.292$), but the correlation was significant in the Blitz tournament analysis ($r_{(11)} = -0.651, p < 0.05, r^2 = 0.423$).

The fact that the standard time Elo-EBPM correlation was not significant is potentially surprising, because the Elo ratings would have been based on the players’ previous performances in standard time events. However, as Vaci et al. (2014) pointed out, studying highly-selected groups of experts can suffer from range restriction effects. So, weak correlations in a group selected from only among the very highest-rated chess players is reasonable.

But, given that logic, it is perhaps even more interesting that the Blitz Elo-EBPM correlation was significant. This suggests that within this group of highly-expert players, the relatively

small differences in expertise was associated with changes in the susceptibility to time pressure induced performance degradation.

Such a connection between chess expertise and relative resistance to time pressure effects is inconsistent with van Harreveld, Wagenmakers, and van der Maas's (2007) finding that strong chess players' ratings will become less predictive of their performance as they play in events that force them to play faster. More data will be required to resolve the true relationship between a chess player's rating and their relative resistance to time pressure effects.

Discussion

In both aviation and competitive chess, it is justifiably assumed that developing a level of expertise through training and practice is important. As with pilots flying military missions or commercial aircraft, the chess players in this study can be considered experts. Indeed, the chess players in this study must be considered at the most extreme high end of chess playing expertise. The analogous level of expertise in piloting would be difficult to define, but it would certainly be greater than simply qualifying to be a military or commercial aviation pilot.

One aspect of expert performance in both domains would be well-developed pattern recognition (e.g., Burns, 2004; Gobet & Simon, 1996; Kaber & Endsley, 1997). That is, the ability to quickly "size up" a situation in order to respond appropriately. It is expected that an expert will very quickly, even immediately, know what to do in situations where a less expert person would require thinking time to assess different aspects of the situation and carefully think through the implications of their combination to select an appropriate action. The distinction between such "fast" versus "slow" processes is common in modern cognitive psychology (e.g., Evans, 2003; Gobet & Simon, 1996; Kahneman, 2011; Moxley, Ericsson, Charness, & Krampe, 2012; Schneider & Shiffrin, 1977; van Harreveld et al., 2007; Wan, Nakatani, Ueno, Asamizuyi, Cheng, & Tanaka, 2011).

Because the time available to think is seriously curtailed or even eliminated, it is the "fast" cognitive processes of experts that are challenged by playing blitz chess or dealing with sudden situations after an automation failure. As noted above, earlier research examining the effect of playing speed on chess performance of expert players has been mixed (e.g., Calderwood et al., 1988; Chabris & Hearst, 2003). But, in the present study, the limitations of such capabilities have been clearly demonstrated. Dealing with the extreme demands of blitz chess, even a group selected from the most expert players in the world not only produced a statistically significant increase in their tendency to select weaker moves; it was a large effect with the size of the expected blunder more than doubling.

This result would probably not surprise the chess players that participated in the events analysed. For example, one of the competitors, the former world chess champion Garry Kasparov, noted that time pressure posed a big challenge to even his chess playing; "The worst enemy of the strategist is the clock. Time trouble, as we call it in chess, reduces us all to pure reflex and reaction, tactical play. Emotion and instinct cloud our strategic vision when there is no time for proper evaluation. Even the most honed intuition can't entirely do without accurate calculations. A game of chess can suddenly seem like a game of chance." (Kasparov, 2007, pp. 45-46)

What does this mean in the aviation domain? It strongly suggests that we cannot expect to just train pilots to a degree of expertise where they can be confidently expected to jump into an unexpected automation failure and intuitively react with an optimal response while under time pressure. The present results suggest that either the automation must be so complete and reliable that we can remove the pilot entirely, or we should design systems that keep the pilots in-the-loop enough that they have a better understanding of the on-going situation and a better chance to bring their expertise to bear in situations where the automation cannot cope. If an automation failure occurs while the pilot is still somewhat engaged in the task, the requirement to perform a complete and immediate analysis of the situation from scratch is diminished which should likewise reduce the experience of time pressure.

Certainly better displays and improved communication between the automation and the pilots should also be helpful, but it is doubtful that the system designer or the real-time automation can be expected to predict the unexpected situation well enough to provide the best display to support a previously disengaged human's quick and accurate appreciation of what should be done. Indeed, if the automation had such clear information to give to the human, it would probably be able to handle the situation itself without human intervention.

Perhaps no perfect solution exists for the current automation-failure challenge, but it might be worth investigating whether aviation automation designs that allow, or even encourage, complete task disengagement by the human operator should be avoided (Casner, Geven, Recker, & Schooler, 2014; Ebbatson, Harris, Huddleston, & Sears, 2010; Kaber & Endsley, 1997; Welford, 1958). Perhaps most tellingly, Onnasch, Wickens, Li, and Manzey (2014) conducted an extensive meta-analysis of the impact of different levels of automation on human performance and one of the key findings was degradation of the human's situation awareness and system failure performance as the degree of automation increased.

Therefore, if the human pilot or operator is going to be the final line of defense to ensure system effectiveness or safety, then semi-automated systems should be better designed to maintain on-going human-interaction so that any automation disengagement would be less likely to produce sudden time pressure on the human to figure out what is happening and then what to do.

That is too much to ask, even from experts.

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