Thailand Statistician
October 2026; 24(4): 1042-1065
http://statassoc.or.th
Contributed paper

On Identifying the Factors Responsible for Frontal Lobe Dysfunction of the Human Brain: An Application of Multi-Event Survival Analysis to Wisconsin Card Sorting Data

Anirban Dutta*[a], Jonali Gogoi [b] and Dibyojyoti Bhattacharjee [b]

[a] Department of Statistics, Centre for Distance and Online Education, Assam down town University, Assam, India.

[b] Department of Statistics, School of Physical Sciences, Assam University, Silchar, Assam, India.

*Corresponding author; e-mail: anirban7991@gmail.com

Received: 23 January 2025
Revised: 29 April 2026
Accepted: 14 June 2026

Abstract

The frontal lobe, located in the anterior region of the brain, plays a crucial role in facilitating cognitive functions. Its vulnerability to injuries due to its location can lead to impaired decision-making, increased risk-taking behaviour, and diminished working memory performance. The extent of frontal lobe dysfunction is often difficult to detect with advanced imaging techniques; thus, researchers rely on low-tech neuropsychological evaluations to assess cognitive deficits and functional impairments. One such tool is the Wisconsin Card Sorting Test (WCST), where participants encounter many errors throughout the test's evaluation process. An individual's performance in WCST can be considered a case of a multi-event survival process, given that the participant may experience numerous failures during the test. The study investigated the influence of various socio-demographic and lifestyle factors on the frequency of errors and, consequently, the degree of front lobe dysfunction. The Andersen-Gill (AG) model is implemented, and it revealed that alcohol abstinence and self-confidence in one's working memory significantly affect the frequency of errors observed in the WCST. Future research should focus on exploring additional factors to enhance the models' ability to capture significant patterns in error risks and shed light on various dimensions of assessing individuals' cognitive flexibility.

Keywords: Survival analysis, multi-event analysis, psychology, short term memory, human brain

1. Introduction

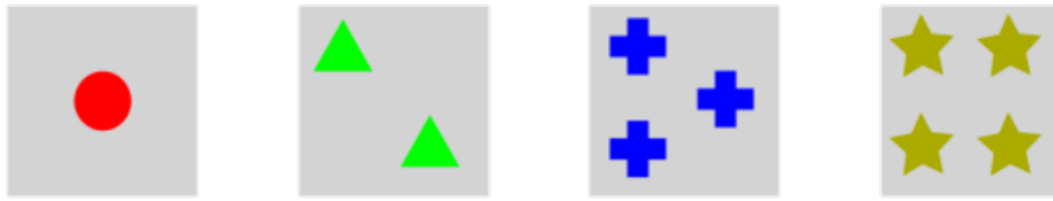
The human mind represents a complex juncture of emotions, logic, intuitions, conscious thoughts, subconscious impulses, perceptions, cognitive processes, and various other executive functions. It is not feasible to directly quantify these facets of the human brain; instead, multiple scales and assessments have been devised to scrutinise these capabilities and different methods to regulate them to the greatest extent possible (Franz 2021).

"It's your frontal lobe that changes your mind, that is, it makes the brain work in different sequences, patterns, and combinations."

~You Are the Placebo: Making Your Mind Matter (Dispenza, 2014)

The frontal lobe lesion is more common than the other parts of the human brain. It is the brain's largest lobe and functions as the central hub for behaviour, emotional control, and personality (Sendic, 2023). Although the frontal lobe is not solely responsible for memory, it plays an essential role in forming and retrieving memories. This type of memory is crucial for tasks that require holding and manipulating information over short periods. Lesion to this part of the brain can lead to various complications, such as short-term memory loss, paralysis, adynamia, disinhibition, Broca's aphasia, and other cognitive dysfunctions (Queensland Health 2022). There are no direct medical tests specifically for diagnosing frontal lobe dysfunction. Instead, clinicians often use psychological scales and neuropsychological assessments to evaluate cognitive deficits (Anderson et al., 1991; Stuss et al., 2000). One such tool is the Wisconsin Card Sorting Test (WCST), which evaluates cognitive flexibility, problem-solving skills, and the ability to adapt to changing rules. Performance on the WCST can yield significant insights into the operational status of the frontal lobe, as it necessitates the incorporation of memory and executive function competencies (Pirau and Lui 2023). A lower score or a higher number of errors on the WCST may indicate impaired frontal lobe function, leading to difficulties with abstract reasoning and cognitive flexibility (Landry and Mitchell 2021, Kohli and Kaur 2006).

The WCST, developed by Grant and Berg (1948), is a neuropsychological tool. It determines the functioning ability of the frontal lobe, thus assessing cognitive flexibility, abstract reasoning, and the ability to shift strategies while measuring attention and concentration. During the assessment, participants are presented with a sequence of 4 reference cards, each distinguished by three categories: colour (red, green, blue, or yellow), shape (circle, triangle, plus, or star), or number of shapes in a card (1, 2, 3, or 4). Participants are tasked with matching the stimulus cards to the reference cards without any indication of the correct matching criteria.



Card no.1 Card no.2 Card no. 3 Card no. 4

Reference Cards



Stimulus Card

Figure 1. Reference and stimulus cards in the WCST

The stimulus card in the aforementioned scenario matches the fourth card on the above row if the shape rule is followed. If the card rule is colour, then it matches card number one; if it is number, then card number two. The test administrator offers feedback on the correctness of responses based on the predetermined category. The administrator modifies the matching rule at specific intervals. This procedure evaluates the participants' ability to transition cognitive patterns and their organised mental performance. Initially intended for individuals with brain injuries, the test has now become prominent in contemporary times, having been adapted and expanded to assess individuals on attention, persistence, memory capabilities, and cognitive flexibility (Teubner-Rhodes et al. 2017, PsyToolkit 2021). The WCST can be conducted in a traditional paper-based format or computerised variations (Heaton 1993, Heaton 2003, Kopp 2020, Steinke 2021).

This study employs the WCST to assess the determinants that influence the chances of errors among the participants, specifically the diverse factors that affect cognitive flexibility and abstract reasoning. Rather than analysing errors for each individual separately, the study investigates the error patterns across a single cross-section of participants in order to comprehend collective trends and factors that may contribute to the risk of error. Conventional methodologies employed in WCST analysis were deemed unsuitable for this approach, as they generally concentrate on isolated errors or individual performances. Accordingly, the study opted for multi-event survival analysis, which facilitates a thorough examination of the timing and occurrence of multiple errors within the cohort. This methodology further permits the identification of various factors that impact error risk and offers a detailed understanding of how these elements influence cognitive processes over time.

Multi-event survival analysis (Recurrent Survival Analysis) is a widely used method, particularly within the domain of medical sciences. This approach enhances traditional survival analysis methods by accommodating numerous events per individual, such as multiple hospitalisations, recurrent cardiac arrests, disease relapses, and other similar scenarios. An essential aspect of survival analysis is its ability to handle censored cases (Yin and Chou, 2023). Multi-event survival analysis represents a robust statistical technique used to analyse the timing and occurrence of recurring events. Models for multi-event studies consider the interrelation between events within the same subject, offering insights into the factors influencing the risk and timing of subsequent events. These models facilitate the prediction of individual risks, the comparison of event rates across groups, and the understanding of how covariates affect the recurrence process. By capturing the dynamic nature of recurring events, this analytical framework offers valuable applications across domains such as medicine, engineering, and the social sciences, where the timing and frequency of events are significant.

This study attempts to examine the factors influencing error rates in the WCST by surveying a group of participants. Through administering the WCST and collecting demographic and lifestyle data, the study seeks to identify critical factors that may impact performance on this cognitive assessment. The findings will contribute to a better understanding and explore the relationship between various personal factors and the extent of frontal lobe dysfunction.

2. Literature Review

The utilisation of survival analysis in the field of psychology has experienced growth throughout the years. This methodology proves to be highly beneficial for psychologists, as it offers a more fitting analysis concerning treatment efficacy compared to conventional analytical methods (Page 1998). An additional crucial factor pertains to instances of censoring and proportionality; various types of clinical and psychological experiments effectively address these issues by efficiently applying survival analysis tools (Prinja et al. 2010).

Landau (2002) presented a demonstration showcasing the utility of survival analysis techniques in psychological contexts. The methodologies for nonparametric and semiparametric survival analysis were employed, along with their software implementations. Maier and Smith (1999) applied Cox regression models to ascertain the psychological predictors of mortality in the elderly. The researchers assessed 17 indicators of psychological functioning related to intellectual abilities, personality, subjective well-being, and social relations concerning mortality. 11 of the 17 indicators were identified as risk factors for mortality, and 6 remained significant after controlling for age in the study. A study conducted in Tanzania by Elahi et al. (2023) evaluated the outcomes of traumatic brain injury (TBI) patients who underwent surgery compared to those who did not. Using Kaplan-Meier (KM) plots and Cox Proportional Hazard Models (CPHM), the authors found that surgical intervention was associated with improved outcomes, particularly for patients with moderate TBI. This suggests that surgical treatment may be valuable for TBI patients in low and middle-income countries. In a separate study by Ninomiya et al. (2024), the researchers sought to investigate the impact of cognitive load and working memory on the effectiveness of identifying superior choices. The findings suggest that higher cognitive load enhanced the efficiency of discovering alternatives, particularly among participants with high working memory capacity.

The WCST (Grant and Berg, 1948), a test designed for the evaluation of working memory and cognitive flexibility (Howard et al. 2020, Kolakowsky-Hayner 2011), can now be conducted with a 64-card variation, initially developed as a 128-card assessment and now available in a computerised format (Kongs et al., 2000). The outcomes from both formats yield comparable results. However, it is recommended to establish new standards specifically for the computerised version due to its advanced digital interface (Fortuny and Heaton 1996, Feldstein et al., 1999, Steinke et al. 2021). Significant research has been conducted on the WCST examination, notably by Kopp et al. (2019), who computed the test's reliability in line with clinical standards. In a separate study by Kohli and Kaur (2006), the implementation of WCST in the Indian demographic was explored. The findings revealed that, unlike Western demographics, variations in WCST scoring parameters are minimal yet statistically significant, except for the number of accurate responses. The authors underscored the examination-focused nature of educational institutions in India, which offer limited opportunities for personality growth, creativity, and refinement of social skills. Lange et al. (2018) conducted a comprehensive analysis of the WCST literature pertaining to individuals with Parkinson’s Disease (PD). Their conclusions suggest that impaired WCST performance can be indicative of significant executive dysfunction in PD. Another analysis of the diagnostic accuracy of the WCST concerning frontal and lateralized-frontal brain injuries was conducted by Demakis (2003). The research demonstrates that WCST scores exhibit sensitivity to damage in the frontal lobes. In the field of clinical psychology, Greve et al. (1999) examined the relationship between factor structure and the progression of stroke rehabilitation using the WCST.

Another study by Somsen et al. (2000) focused on the performance, response speed, and heart rate of adolescents undertaking the task. In a study by Lougheed et al. (2019), a multilevel survival analysis (MSA) was conducted to examine the timing of recurrent behaviours in children. The findings suggest that MSA represents a versatile analytical approach for studying observational data and has the potential to provide valuable insights into the dynamics of children’s behaviour.

Reviewing the literature, this study aligns with the dimensions used to assess the WCST, which conventionally comprises two distinct categories: perseverative and non-perseverative errors. The frequency and pattern of these errors often reflect the short-term memory capacity of the subject involved in the WCST. These errors are noted at various time intervals while a particular participant engages in the task. The game’s rules change after a set number of trials, and participants may make

errors before or after the rule change, depending on the operational capacity of their frontal lobes. This situation illustrates a remarkable application of multi-event survival analysis, as each error can be treated as an instance of the event of interest. The diverse methodologies employed in multi-event survival analysis can be systematically organised, and it can be hypothesised whether factors such as gender, age, education, place of residence, alcohol consumption levels, medication use, stress levels, and self-confidence in working memory influence the frequency and quantity of errors made. Surprisingly, to the best of current knowledge, most prior studies analysing performance on the WCST have relied on aggregate error counts or summary indices. In contrast, the present study models error occurrences as recurrent time-to-event data using multi-event survival analysis techniques. The application and comparison of the Andersen-Gill (AG) model, the Prentice-Williams-Peterson models (gap-time and total-time formulations), the Wei-Lin-Weissfeld model, and the shared frailty model provide a dynamic and intensity-based analytical framework for examining cognitive performance. By incorporating the temporal structure and recurrence patterns of errors, this approach extends conventional neuropsychological analyses and offers a more refined quantitative perspective on executive functioning and cognitive flexibility.

3. Objective of the Study

The research gap for this study pertains to two main aspects. First, it involves quantifying the time to error occurrence during the testing process throughout the assessment. Second, it focuses on identifying various lifestyle and social factors that influence the frequency of such errors, thereby facilitating an understanding of the degree of frontal lobe dysfunction and the factors that contribute to it. The primary objective of the research can be placed as follows:

To identify the significant socio-demographic and lifestyle factors that impact the frequency of error risks in the WCST, impacting the extent of dysfunction in the brain’s frontal lobe.

4. Methodology

Survival analysis is a statistical approach used to analyse the time until an event of interest, often called the "failure" event, occurs. Within the framework of our investigation, survival analysis can be utilised to examine the timing of errors or responses made by participants throughout the test. When an individual experiences multiple events within a specific study period, this is an example of multi-event survival analysis (van Houwelingen and Putter 2012, Kleinbaum and Klein 2012).

Multi-event survival analysis: A statistical methodology used to examine time-to-event data in which individuals may encounter repeated events within a specific timeframe (Yin and Chou 2023). In contrast to traditional survival analysis, which primarily focuses on the duration until a single event (e.g., death or failure), multi-event survival analysis addresses scenarios in which events can occur repeatedly (e.g., hospital readmissions, machine failures, or recurrent illness). To provide a concise overview of the mean frequency of errors an individual experiences over a specific timeframe, the mean cumulative function (MCF) methodology is employed.

The MCF, introduced by Nelson (1988) and further developed by Lawless and Nadeau (1995), is a statistical method used to estimate the average number of errors committed by the individuals participating in the WCST exposed to censoring events like participants dropping out and conclusion of the test. Assuming independence between error time and censoring time, the MCF models the accumulation of events over a given period (Donaldson et al. 2007). In the study context, the MCF can be applied to track the accumulation of errors throughout the test.

To define the MCF, one must examine a cohort of n subjects who are followed up on over time and may experience errors at particular times $t_1, t_2, t_3,$ and so on up to t_N. At distinct point t_j, the MCF is calculated as

$$MCF\left(t_j\right) = \sum_{k=1}^{j} \frac{e_k}{n_{k-1}}, \tag{1}$$

where e_k is the number of errors occurring at the time t_k, and n_{k-1} is the number of persons at risk just beyond time t_{k-1}. The number of individuals at risk at time t_{k-1} is equal to the total individuals initially at risk minus those who are censored prior to time t_{k-1}. In this circumstance, the cohort decreases only when a participant withdraws from the test midway or when the test is terminated. (Donaldson et al. 2007).

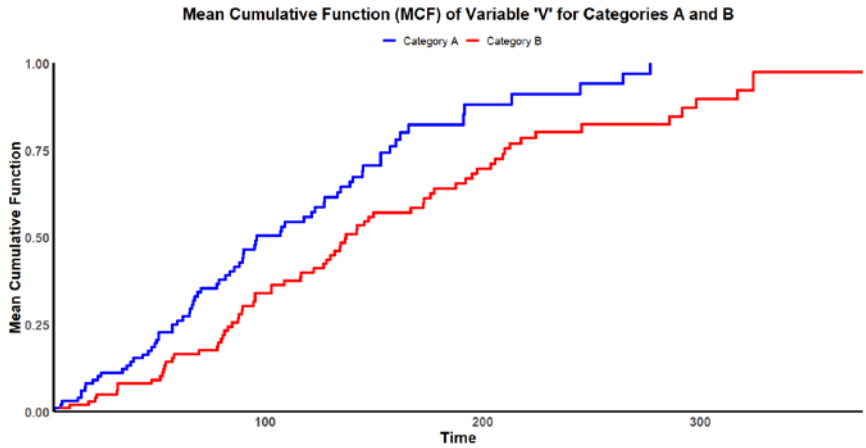


Figure 2 Mean cumulative function (MCF) of a dummy variable V

To better comprehend this, the MCF for a dummy variable 'V' is plotted with categories A and B. This variable 'V' is considered a factor of individuals participating in the WCST. In the resulting plot, the MCF for category A (in blue) and category B (in red) diverges, indicating that individuals in category A tend to exhibit a more significant cumulative occurrence of errors than those in Category B. To determine whether this divergence is statistically significant, further analysis is needed to better understand the covariate's impact on participants' error risk.

Utilising the MCF to explore the overall pattern of errors in the WCST, the AG model is employed for more detailed regression-based inference. While the MCF provides a nonparametric description of the cumulative occurrence of errors over time (Nelson 1988), it does not allow direct quantification of covariate effects. The AG model extends this analysis by modelling the intensity of error occurrence as a function of socio-demographic and lifestyle factors, thereby analysing their association with error risk (Andersen and Gill 1982).

Although errors in the WCST may exhibit temporal or cognitive dependence due to learning effects, fatigue, or strategy adaptation across trials, the primary objective of this study is to draw population-level inferences about covariate effects rather than to model individual-specific learning trajectories. Within this framework, the AG model provides a parsimonious and widely used approach for analysing recurrent-event data. To assess the sensitivity of the results to the conditional

independence assumption underlying the AG formulation, additional recurrent-event models that explicitly account for event dependence and unobserved heterogeneity, the Prentice-Williams-Peterson (PWP) models (both total time and gap time versions), Wei-Lin-Weissfeld (WLW) Model, and frailty models, are also employed. The use of these complementary models allows evaluation of whether accounting for dependence materially alters inference regarding the determinants of WCST errors.

The AG model is used here to analyse errors in the WCST because it is well-suited to handling complex, recurrent-event data. As an extension of the Cox proportional hazards model, it is particularly well-suited for WCST analysis because it can effectively handle multiple errors, treats recurrent events as repeated independent occurrences of the same event type, and uses a counting process approach. The model's ability to incorporate time-varying covariates is crucial for modelling changing conditions during the WCST. Furthermore, the Andersen-Gill model employs an intensity-based approach, enabling a detailed analysis of the rate at which errors occur over time, which is especially valuable for understanding the complex patterns of errors in WCST performance. The model's flexibility in the baseline hazard function contributes to more robust and accurate estimates of error patterns and their underlying factors. Lastly, its efficient use of all available data, including information from censored observations, ensures a comprehensive analysis of WCST performance (Andersen and Gill 1982, Therneau and Grambsch 2000, Amorim and Cai 2015). The intensity function of the AG model is given by

$$\lambda_i(t) = Y_i(t)\lambda_0(t)e^{X_i\beta}, \tag{2}$$

where $Y_i(t)$ is the left continuous at-risk process, which is unity whenever the subject is at risk for an event, $\lambda_0(t)$ is the baseline hazard, X_i is the treatment group, and $\beta's$ are the regression coefficients (Al-Khalidi et al. 2011).

The AG model is known for its flexibility in handling diverse follow-up durations and censoring scenarios. It is widely used in medical research to analyse repeated hospital admissions, disease recurrences, and other recurrent events, providing insights into factors that influence the risk of such events over time. In the WCST, the AG model treats each error occurrence as an independent event and can handle time-varying covariates, making it useful for analysing how error risk changes across different time frames of the test.

The Prentice-Williams-Peterson (PWP) models are stratified Cox approaches for recurrent event data, with two main variants: the total time and the gap time models. The PWP total time model considers the time since the study began (total time) for each event (errors), treating the time scale as continuous across events. Conversely, the PWP gap time model resets the time at each event (error), focusing on the time elapsed since the last event.

If a trial with two treatment groups and no further covariates are considered, in the total time model, the hazard for an individual i for the j^{th} recurrent event is modelled as

$$\lambda_{ij}(t) = \lambda_{0j}(t)\exp\left(\beta_j X_{ij}\right);\ i = 1,\ldots,n,\ j = 1,\ldots k_i,\ k_i \le k, \tag{3}$$

whereas in the gap time approach, the hazard is modelled as

$$\lambda_{ij}(t) = \lambda_{0j}\left(t - t_{j-1}\right)\exp\left(\beta_j X_{ij}\right);\ i = 1,\ldots,n,\ j = 1,\ldots k_i,\ k_i \le k, \tag{4}$$

It is seen that the above models are similar to the standard Cox model (Ozga et al. 2018), but for each recurrent event $j = 1,\ldots,k_i$, a separate hazard function is shown with its baseline hazard λ_{0j} and a regression parameter β_j.

Both models account for the within-subject correlation of recurrent events and allow for different baseline hazard functions for each event type. They are suitable for studies involving multiple ordered recurrent events, such as repeated errors in the WCST.

The Wei-Lin-Weissfeld (WLW) model is also a stratified Cox approach that presents an alternative methodology for analysing recurrent event data, treating each recurrent event as an individual stratum within a CPHM framework. This approach enables the specification of unique baseline hazard functions for each stratum (event type) while assuming consistent effects of covariates across all strata.

In the general framework of the WLW method, it is assumed that each of *N* subjects is monitored for the occurrence of K distinct events, with the possibility of right censoring for the times to any of these K events. When employed to analyse differences between groups, the hazard function for the time to the k^{th} event is specified as

$$\lambda_k\left(t;Z\right)=\lambda_k\left(t\right)e^{\beta_k Z}, \tag{5}$$

where Z denotes the treatment group, $\beta_1,\ldots\beta_k$ are unknown regression coefficients, $\lambda_k\left(t\right)$ are the unspecified baseline hazard functions, which can be different among the K events (Li and Lagakos, 1997).

The WLW model offers the advantage of managing tied event times effectively and is relatively straightforward to implement. Its applicability is particularly notable in clinical research settings where patients may encounter diverse event types, prompting researchers to explore the impact of covariates on each event category separately. In the study context, this method gives different weights to different data points based on their variance and accounts for heteroscedasticity, where the variability of errors might differ across conditions or subjects, ensuring that the model adequately reflects these differences.

The frailty model is also an extension of the CPHM that introduces a random effect (frailty) to account for unobserved heterogeneity among individuals. This model is beneficial when there is a belief that unmeasured factors influence the risk of the event. By incorporating the frailty term, the model can account for the correlation between recurrent events within the same individual (Balan and Putter 2020).

In the univariate frailty model, the hazard of an individual with frailty Z is specified as

$$\lambda\left(t|z\right)=Z\lambda\left(t\right), \tag{6}$$

If the covariates (X_i) are present along with their coefficients (β_i), then the frailty model is written as

$$\lambda\left(t|z\right)=Z\lambda_0\left(t\right)\exp\left(\beta_i^{'}X_i\right). \tag{7}$$

The frailty model is widely used in survival analysis for recurrent events, providing more accurate estimates by accounting for individual-level variability in the hazard function. In this situation, this model can account for individual differences in error risk that are not explained by observed variables, recognising that some participants may be inherently more prone to errors than others due to unmeasured factors. For detailed mathematical computations for all models used, see Ozga et al. (2018), Wu and Little (2010), and Balan and Putter (2020).

5. Data Source

Our study utilised primary data collected through an online platform, psytoolkit.org (Stoet 2010, 2017). This website allows the users to design and implement a comprehensive data collection strategy that combines a questionnaire with the WCST. The data collection process was structured in two main

parts. First, participants were presented with a questionnaire designed to gather socio-demographic and lifestyle information.

Participants in the study were asked to provide information including name, age, gender, educational level, place of dwelling, medication use, and alcohol consumption (categorised as “never”, “maximum four drinks”, “maximum ten drinks”, and “more than ten drinks” in a month). Additionally, participants were asked to complete the Perceived Stress Scale (PSS) and the General Self-Efficacy Scale (GSE) to measure their stress levels and self-belief. (Details provided in Appendix I). The PSS and GSE scores were categorised into ordinal groups for analytical purposes. While categorising continuous measures may reduce statistical efficiency, this approach enhances interpretability and allows comparison across psychologically meaningful levels. Moreover, categorisation avoids imposing a strict linearity assumption between scale scores and error intensity.

Secondly, participants were immediately directed to complete the WCST after responding to the questionnaire. This sequential design allowed us to directly link each participant’s socio-demographic and lifestyle data to their WCST performance. In the context of this study, the “event” is defined as the occurrence of an error in the WCST. The “time” variable was operationalised as the time taken to make each error during the test. This approach permits the analysis of the frequency of errors and the temporal patterns of error occurrence throughout the test.

Data were collected by embedding the WCST in the questionnaire and distributing it via psychtoolkit.org to potential participants. This method allowed for broad reach and enabled participants to complete the study at their convenience, potentially reducing barriers to participation. The statistical computations were executed using R software version 4.3.3, using packages such as “survival”, “frailtypack”, and “dplyr” and their dependencies.

A total of 263 individuals participated in the test, with varying demographic characteristics. This primary data collection method provided a rich, multifaceted dataset that combined detailed individual characteristics with precise WCST performance metrics, enabling a comprehensive analysis of factors influencing cognitive flexibility and error patterns. A summary of the dataset containing a few participants is depicted in Table 1.

Table 1 presents the error timing data for ten randomly selected participants from a larger pool of 263 individuals (only for the purpose of description). Each column displays the occurrence of the error corresponding to the respondent's unique ID. It is important to note that the number of errors and the time to the last error vary among participants, reflecting individual differences in frontal lobe functioning.

The computerised version of the WCST imposes a 10-second maximum time limit per trial. Consequently, the error times in the data set are constrained to a range of 0 to 600 seconds, corresponding to the maximum possible duration of 60 trials. As the data were collected through an online platform, participation was voluntary and self-selected, which may introduce potential selection bias. Although embedding the WCST within the questionnaire ensured linkage of responses and reduced missing data, testing conditions could not be fully standardised across participants. External distractions, differences in device type, or internet connectivity may have influenced task performance. While basic data screening procedures were conducted to ensure completeness and consistency, these uncontrolled environmental factors should be considered when interpreting the findings.

Table 1 A summary of the error timing of the individuals who participated in the WCST (10 individuals randomly taken out of 263 participants)

Serial Number	ID number	Time to i^{th} error (in seconds)					
		1^{st} error	2^{nd} error	3^{rd} error	4^{th} error	…	n_i^{th} (last) error
1	01	3.2319	33.9293	40.3791	49.3570	…	318.1467
2	02	3.2130	10.2681	32.5128	40.0150	…	307.5137
3	03	13.5054	15.6020	33.6708	42.9650	…	293.8981
4	04	11.7686	25.1838	34.3668	36.6271	…	298.6260
5	05	6.1988	26.6197	28.7512	54.0877	…	328.9227
6	06	36.0973	57.2853	65.0880	91.3287	…	325.0128
7	07	21.8665	39.2930	54.3852	56.1018	…	306.3670
8	08	21.6130	22.3036	59.0129	71.9058	…	328.4588
9	09	34.5850	52.0159	60.4868	79.0436	…	318.0928
10	10	10.0881	27.2886	53.6970	63.4387	…	310.1752

6. Calculations and Results

This section first presents the descriptive and model-based statistical findings, followed by brief interpretation in relation to the study objectives.

Based on the dataset, the MCF is plotted to visualize the cumulative frequency of error occurrences across the various factors considered for individuals participating in the WCST. The following figures depict the MCF curves for the different groups.

These MCF plots illustrate the accumulation of events over time across various social and lifestyle factors in the study. Education levels show slight variations, with high school potentially associated with lower error accumulation. Gender appears to have minimal impact on error occurrence rates. Alcohol consumption habits demonstrate minor differences, with non-drinkers showing a slightly lower cumulative function through the end. Stress levels exhibit some variation, with very high and high-stress groups showing slightly lower cumulative functions, particularly in the latter half of the study period. Medicine use presents a noticeable difference, with those not taking medicine consistently showing a higher cumulative function throughout the study, suggesting more frequent event occurrences. Self-belief levels display interesting patterns, with below-average self-belief associated with faster error accumulation early on, while very high self-belief shows the slowest accumulation until around the study's midpoint. Overall, while these graphs reveal some differences across categories, many lines converge by the end of the study period, indicating that the long-term cumulative effects may be similar across groups. It is important to note that while visual differences are observed, statistical testing would be necessary to determine the significance of these variations, and the specific nature of the events being studied would provide crucial context for interpreting these results meaningfully.

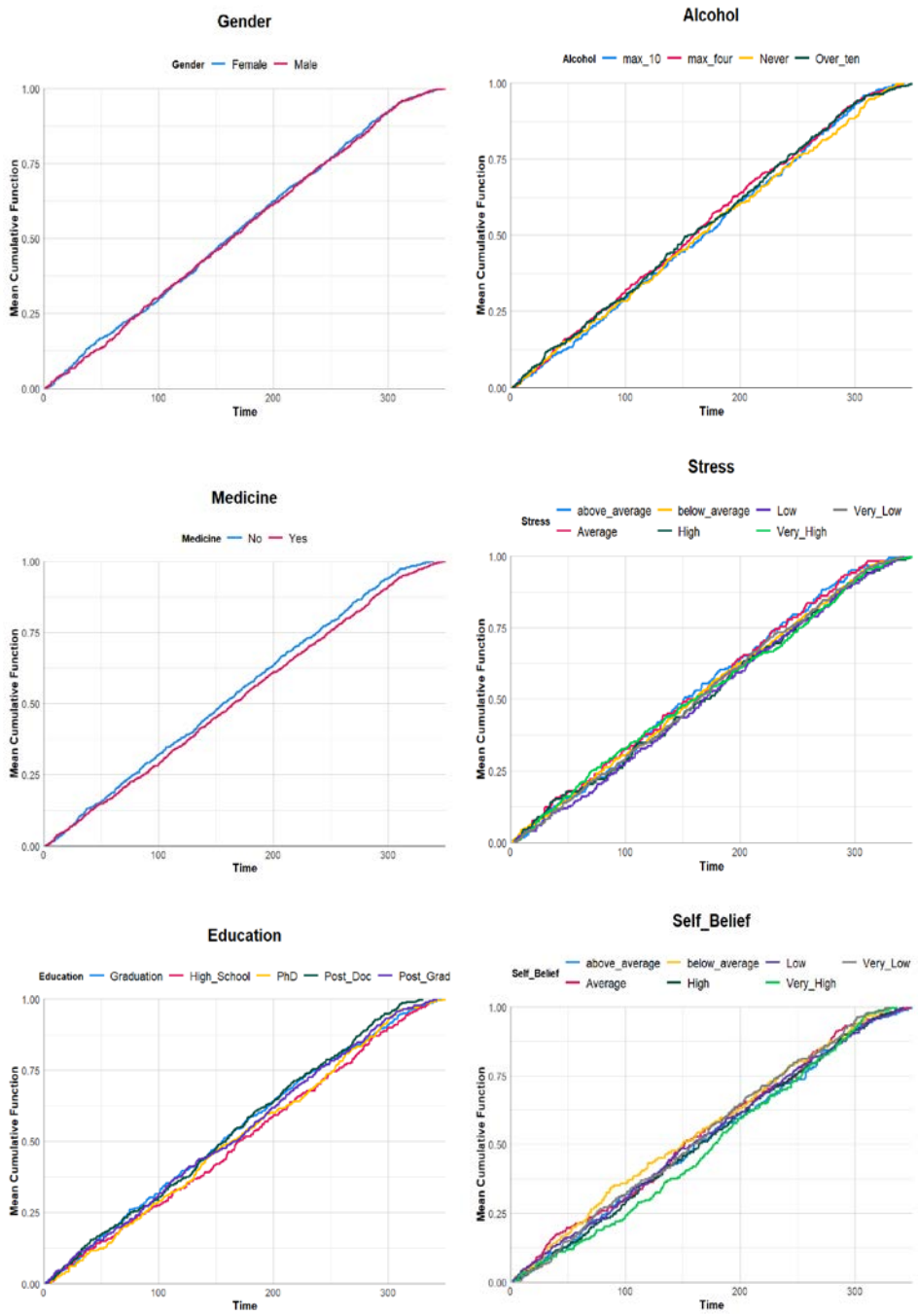


Figure 3 Mean cumulative functions of factors influencing WCST errors

The research delves further into examining the potential influence of socio-demographic and lifestyle factors on the frequency of errors recorded during the WCST by participants. The study utilised the application of the AG model to identify the influence of these factors.

The AG model extends the CPHM (Ozga et al. 2018), in which the proportional hazards (PH) assumption is a key criterion. Thus, the PH assumption assesses whether the effect of a factor remains constant over time. A p-value of less than 0.05 signifies that the specific variable exhibits time-dependent effects, indicating a violation of the PH assumption. In contrast, a p-value greater than 0.05 indicates no evidence of a violation, and the PH assumption may be considered reasonable. In such cases, Cox-based recurrent-event models can be appropriately applied. Table 2 presents the results of the proportionality hazard assumption test using the Schoenfeld residuals method.

Table 2. Proportionality Hazard (PH) assumption test for checking the time dependency effect

Factors	Chi-Square	Degrees of freedom	p-values
Gender	0.627	1	0.43
Age	1.406	1	0.24
Medicine	0.915	1	0.34
Alcohol	1.606	3	0.66
Stress	2.109	6	0.91
Self-Belief	3.721	6	0.71
Education	5.281	4	0.26
Global	14.404	22	0.89

Table 2 indicates that the p-values for all factors exceed 0.05, implying that the assumption of proportional hazards is not violated. Consequently, it can be inferred that the factors are not dependent on time. Although WCST performance may involve distinct cognitive stages, the present analysis considers the overall time-to-error process. The proportional hazards assumption is therefore evaluated over the full observation period and is not violated. Future work may investigate phase-specific dynamics using stratified or multi-state survival models.

Having satisfied the PH assumption, the study applies the AG model to analyse the influence of the covariates on the time-to-error occurrence. Table 3 below shows the outputs of the AG model.

From the table, the AG model identifies that the individuals categorised under the group of never consuming alcohol exhibit a noteworthy impact (p-value = 0.0356), with a hazard ratio of 0.9105, implying that abstaining from alcohol is linked to decreased chances of errors in contrast to the reference category.

Furthermore, individuals holding beliefs of below average (p-value = 0.0290) and low self-belief (p-value = 0.0407) demonstrate substantial impacts, with hazard ratios of 1.124402 and 1.110126, respectively, indicating an elevated risk of errors compared to the standard category. It is to be noted that the p-value for the groups ‘very low’ (p-value = 0.0578) and ‘average’ (p-value = 0.0588) is close to 0.05. Although it does not reach the conventional threshold for statistical significance, it is approaching the point of becoming a significant variable, indicating a potential association that warrants further investigation. From a practical standpoint, the estimated hazard ratios represent relative differences in the instantaneous likelihood of committing an error during the WCST. A hazard ratio greater than one indicates an increased risk of error at any given moment compared to the reference category, whereas a hazard ratio less than one indicates a comparatively reduced risk. For example, the lower hazard associated with alcohol abstinence suggests relatively more stable task performance, while elevated hazard ratios for lower self-belief categories indicate a higher tendency toward error occurrence over time. These interpretations provide a behavioural understanding of how the estimated effects translate into differences in cognitive performance during the task.

Table 3. Results of the AG model employed to identify the impact of the factors

		coefficient	exp(coefficient)	se(coefficient)	p-value
Gender (ref: Female)	Male	0.0386	1.0394	0.0662	0.2121
Age		-0.0014	0.9985	0.0038	0.4333
Medicine (ref: No)	Yes	0.0690	1.0714	0.1098	0.2083
Alcohol (ref: max ten)	Max four	-0.0205	0.9796	0.0847	0.5975
	Never	-0.0937	0.9105	0.0949	0.0356
	over ten	-0.0274	0.9729	0.0943	0.5342
Stress (ref: Above Average)	Average	-0.0231	0.9771	0.1403	0.7354
	below average	-0.0126	0.9874	0.1146	0.8168
	High	-0.1207	0.8862	0.1400	0.1178
	Low	-0.0492	0.9519	0.1245	0.4193
	Very High	-0.0526	0.9487	0.1143	0.3539
	very low	-0.0330	0.9675	0.1180	0.6013
Self-Belief (ref: Above Average)	Average	0.1296	1.1384	0.1305	0.0588
	Below Average	0.1172	1.1244	0.1412	0.029
	High	0.0786	1.0818	0.1197	0.1405
	Low	0.1044	1.1101	0.1032	0.0407
	Very High	0.0718	1.0745	0.1127	0.1773
	very Low	0.1138	1.1205	0.1286	0.0578
Education (ref: Graduation)	High School	-0.016446	0.983689	0.105053	0.6848
	PhD	0.013964	1.014062	0.08744	0.6929
	Post Doc	0.025062	1.025379	0.097391	0.5681
	Post Grad	0.034806	1.035419	0.09691	0.4183

We then analyse the subsequent models, namely the PWP models, which serve as extensions of the Cox regression models. The proportionality assumptions are met; thus, we have applied the Total time method and the gap time method to ascertain whether events rely on preceding occurrences. Table 4 and Table 5 present the Gap time method and the Total time method for the PWP model.

From the PWP models, it is evident that none of the predictors exhibited statistically significant effects in the Gap time model (Table 4). Conversely, within the Total time model, individuals who engage in alcohol consumption exceeding ten times per month ($p = 0.0408$) face an elevated risk of error.

Subsequently, the WLW model was employed, which serves as a variant of the Cox model utilised for assessing recurrent events, analysing each event separately from data alongside random effects. The model was applied to our dataset, yielding the subsequent results.

The output indicates that none of the predictors yield statistically significant findings. The frailty model has investigated potential unobserved heterogeneity in the recurrent event data. The output related to this analysis is presented in the table below.

The table illustrates that none of the predictors exhibited statistically significant effects at a significance level of $p < 0.05$. The frailty parameter, denoted as Theta, is measured at 0.000142052 (p

= 0.2677), indicating limited support for within-subject correlation. The graphical representations of the significant factors are visualised below.

Table 4. Results of the PWP gap time model to identify the impact of the factors

		coefficient	exp(coefficient)	se(coefficient)	p-value
Gender (ref: Female)	Male	0.0418364	1.0427239	0.0800193	0.5156
Age		-0.0002924	0.9997076	0.0047189	0.9448
Medicine (ref: No)	Yes	-0.1284244	0.8794801	0.1366067	0.2973
Alcohol (ref: max ten)	Max four	0.0255340	1.0258627	0.1037256	0.7449
	Never	-0.1422382	0.8674146	0.1171846	0.2208
	over ten	0.1163868	1.1234304	0.1160866	0.2356
Stress (ref: Above Average)	Average	-0.0975646	0.9070438	0.1671611	0.5303
	below average	0.0865997	1.0904600	0.1383047	0.4556
	High	-0.0786022	0.9244076	0.1728013	0.6775
	Low	-0.0676939	0.9345465	0.1522817	0.6316
	Very High	0.0604994	1.0623670	0.1413794	0.6647
	very low	0.0191822	1.0193674	0.1470701	0.9033
Self-Belief (ref: Above Average)	Average	0.1611974	1.1749169	0.1579903	0.2693
	Below Average	0.1467339	1.1580457	0.1767885	0.3333
	High	0.0814173	1.0848234	0.1447331	0.5198
	Low	0.1004431	1.1056608	0.1239977	0.4050
	Very High	0.0511455	1.0524760	0.1346101	0.6447
	very Low	-0.0302703	0.9701833	0.1571636	0.8305
Education (ref: Graduation)	High School	-0.1257593	0.8818271	0.1295711	0.2051
	PhD	-0.0091447	0.9908970	0.1084757	0.9188
	Post Doc	0.0143245	1.0144276	0.1176572	0.9119
	Post Grad	0.1941601	1.2142907	0.1218200	0.0951

Table 5. Results of the PWP total time model to identify the impact of the factors

		coefficient	exp(coefficient)	se(coefficient)	p-value
Gender (ref: Female)	Male	-0.069383	0.932970	0.074118	0.6501
Age		-0.002679	0.997325	0.004173	0.7909
Medicine (ref: No)	Yes	-0.278121	0.757205	0.121058	0.3355
Alcohol (ref: max ten)	Max four	0.113299	1.119967	0.092208	0.4994
	Never	-0.143626	0.866211	0.106740	0.5430
	over ten	0.425694	1.530652	0.106647	0.0408
Stress (ref: Above Average)	Average	-0.172916	0.841208	0.147769	0.5458
	below average	0.178269	1.195146	0.126758	0.4859
	High	-0.048237	0.952908	0.149016	0.9031
	Low	-0.062742	0.939186	0.141080	0.8305
	Very High	-0.144822	0.865176	0.123224	0.6130
	very low	-0.023231	0.977037	0.133802	0.9412
Self-Belief (ref: Above Average)	Average	0.134319	1.143758	0.141752	0.6932
	Below Average	0.425400	1.530203	0.153714	0.2096
	High	0.119400	1.126821	0.131750	0.6540
	Low	0.192427	1.212187	0.116040	0.4628
	Very High	0.159394	1.172800	0.121247	0.5056
	very Low	0.151581	1.163673	0.140051	0.6221
Education (ref: Graduation)	High School	-0.205426	0.814301	0.113932	0.3373
	PhD	0.222826	1.249604	0.098375	0.3440
	Post Doc	0.268114	1.307496	0.106715	0.3175
	Post Grad	0.521109	1.683895	0.108383	0.1294

Table 6. Results for the WLW model to identify the impact of the factors

		coefficient	exp(coefficient)	se(coefficient)	p-value
Gender (ref: Female)	Male	-0.0040188	0.9959893	0.0118872	0.9187
Age		-0.0008300	0.9991704	0.0006891	0.7495
Medicine (ref: No)	Yes	-0.0242998	0.9759930	0.0196865	0.7409
Alcohol (ref: max ten)	Max four	-0.0396706	0.9611060	0.0151821	0.4457
	Never	-0.0489864	0.9521940	0.0170456	0.4109
	over ten	0.0529897	1.0544188	0.0166937	0.3853
Stress (ref: Above Average)	Average	-0.1186105	0.8881536	0.0253430	0.0862
	below average	-0.0088375	0.9912014	0.0206595	0.8839
	High	0.0102620	1.0103148	0.0248576	0.9166
	Low	-0.0090901	0.9909510	0.0225268	0.8893
	Very High	-0.0663539	0.9357996	0.0205027	0.3321
	very low	0.0155884	1.0157105	0.0213276	0.8322
Self-Belief (ref: Above Average)	Average	0.0414497	1.0423208	0.0235560	0.6423
	Below Average	0.0433073	1.0442587	0.0253313	0.5914
	High	0.1343503	1.1437934	0.0217122	0.0623
	Low	0.0325835	1.0331201	0.0187086	0.6042
	Very High	0.1375643	1.1474755	0.0201243	0.1423
	very Low	0.1092683	1.1154616	0.0230246	0.1519
Education (ref: Graduation)	High School	0.0047656	1.0047770	0.0190702	0.9369
	PhD	0.0783679	1.0815205	0.0157648	0.1966
	Post Doc	0.0670849	1.0693863	0.0176206	0.2704
	Post Grad	0.0634165	1.0654706	0.0173805	0.2277

Table 7. Results for the frailty model to identify the impact of the factors

		coefficient	exp(coefficient)	se(coefficient)	p-value
Gender (ref: Female)	Male	0.046673	1.04778	0.07487	0.53302
Age		-0.00222	0.997787	0.004417	0.616
Medicine (ref: No)	Yes	0.102643	1.108096	0.132213	0.43754
Alcohol (ref: max ten)	Max four	-0.02329	0.976984	0.095434	0.80723
	Never	-0.09301	0.911186	0.10707	0.38503
	over ten	-0.00994	0.99011	0.10434	0.92411
Stress (ref: Above Average)	Average	-0.01901	0.981172	0.154397	0.90202
	below average	0.009472	1.009517	0.126525	0.94032
	High	-0.08014	0.922989	0.157877	0.61174
	Low	-0.01834	0.981825	0.137309	0.89373
	Very High	-0.04049	0.960323	0.124811	0.74565
	very low	-0.01707	0.98307	0.129182	0.89484
Self-Belief (ref: Above Average)	Average	0.113314	1.119983	0.142738	0.42728
	Below Average	0.123498	1.131448	0.156765	0.43082
	High	0.096537	1.10135	0.132683	0.46687
	Low	0.110265	1.116574	0.116014	0.34188
	Very High	0.093438	1.097942	0.128570	0.46738
	very Low	0.158668	1.171949	0.147526	0.28214
Education (ref: Graduation)	High School	0.006066	1.006084	0.116555	0.95849
	PhD	0.015773	1.015898	0.096548	0.87022
	Post Doc	0.053800	1.055274	0.108179	0.61896
	Post Grad	0.013347	1.013436	0.108682	0.90226

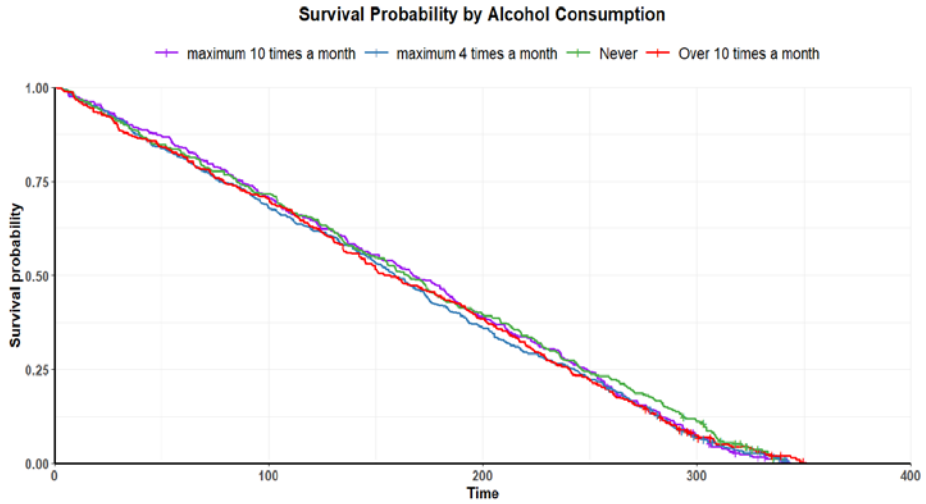


Figure 4. Survival curves for the variable 'Alcohol'

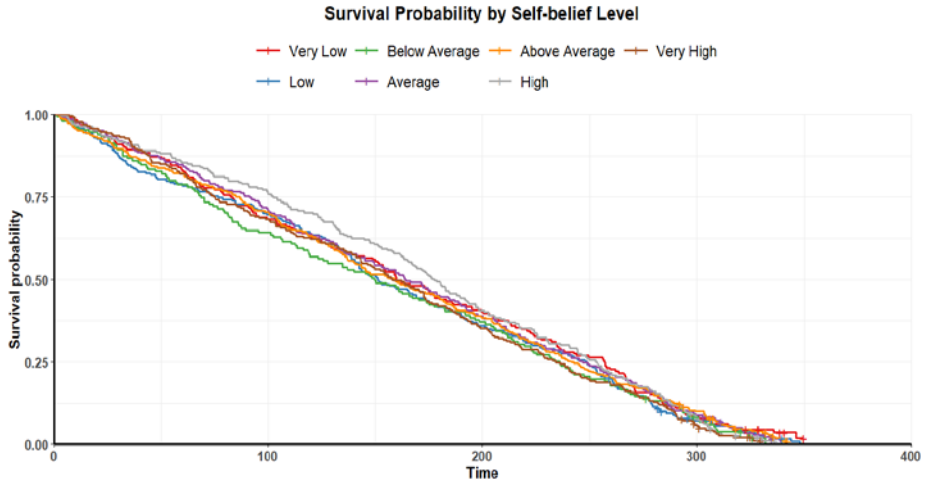


Figure 5. Survival Curves for the variable 'Self-Belief'

The survival probability curves highlight the importance of self-belief and alcohol consumption in forecasting survival outcomes. The classifications of alcohol consumption reveal distinct variations in survival probabilities. From Figure 4, individuals categorised as "Alcohol=Never" demonstrate the highest survival probability over time in comparison to the reference category "Alcohol = maximum 10 times a month", whereas those classified under "Alcohol=maximum 4 times a month" and "Alcohol=Over 10 times a month" exhibit lower survival probabilities. This indicates that abstaining from alcohol or limiting consumption to moderate levels may be beneficial for performance on the WCST test, reflecting reduced frontal lobe dysfunction. Similarly, from Figure 4, it can be said that individuals exhibiting lower self-belief, specifically those classified as "Self-belief = Low" and "Self-belief = Below Average", demonstrate lower survival probabilities as compared to their counterparts.

It is noted that “Self-belief = High” shows a high survival rate, though not significant enough, as suggested by the AG model.

Overall, the graphical depiction of the survival curves affords critical insights that align with the statistical findings derived from the models used. The variations in survival probabilities based on alcohol consumption and levels of self-belief underscore the complex interplay of factors that affect survival outcomes in this investigation.

The results indicate that alcohol abstinence is associated with fewer errors and that low self-belief is linked to higher error frequency on the WCST. These findings align with previous research by other authors, which shows that alcohol consumption (Oscar-Berman 2003, Abernathy 2010) and self-belief (Grimaldi 2015, Rouault 2020, Loo 2021) significantly affect the brain’s frontal lobe function and decision-making capacity. This supports the idea that lifestyle and psychological factors play crucial roles in cognitive performance as measured by the WCST.

7. Conclusion and Discussion

This study advances neuropsychological research by applying multi-event survival analysis techniques to the Wisconsin Card Sorting Test (WCST), an extensively utilised tool for assessing executive functions and cognitive flexibility. By adapting survival analysis methods traditionally used in medical science to psychological assessments, this research demonstrates the potential of interdisciplinary approaches in enhancing our understanding of cognitive performance. The application of survival analysis to the WCST offers unique advantages, including the ability to quantify time to error, analyse recurrence patterns, and identify factors associated with error frequency. This approach provides a dynamic perspective on cognitive performance compared to conventional aggregate scoring methods.

In the preliminary phase, the Mean Cumulative Function (MCF) was employed to examine general patterns of error recurrence in the WCST. While the MCF provided a descriptive overview of error accumulation, it revealed only marginal differences across groups, suggesting the need for regression-based modelling to assess covariate effects more precisely.

Subsequently, multiple recurrent-event survival models were applied, including the Andersen–Gill (AG) model, the Prentice-Williams-Peterson (PWP) models (gap-time and total-time formulations), the Wei-Lin-Weissfeld (WLW) model, and a shared frailty model. The AG model identified alcohol abstinence and lower levels of self-belief as factors associated with differences in error intensity. Specifically, individuals who reported never consuming alcohol showed reduced error risk relative to the reference category, whereas lower self-belief levels were associated with increased error intensity. The PWP models provided additional insight into event-order dependence. While the gap-time formulation did not identify statistically significant predictors, the total-time model indicated elevated error risk among individuals with higher alcohol consumption frequency. The WLW model did not yield statistically significant covariate effects. Furthermore, the frailty model showed a very small and statistically insignificant frailty variance parameter, suggesting limited evidence of substantial within-subject heterogeneity beyond observed covariates.

Overall, the results across different recurrent-event models were broadly consistent, indicating that the main findings are reasonably robust to alternative modelling assumptions. Although moderate concordance values suggest unexplained variability remains, the comparative modelling approach strengthens confidence in the stability of the observed associations. It is important to clarify that, in this study, all WCST errors were treated as recurrent events of a single type. While perseverative and non-perseverative errors may reflect distinct cognitive mechanisms, the present analysis focused on modelling overall error intensity. Differentiating between error subtypes would require a competing

risks or multi-state survival framework, which lies beyond the scope of the current investigation. Future research may extend this framework to examine subtype-specific dynamics in greater detail.

The findings suggest that lifestyle and psychological factors may be associated with variations in WCST error patterns. These observations are broadly aligned with previous literature indicating that alcohol consumption and self-belief or self-efficacy can influence cognitive functioning and decision-making processes. From a neurocognitive perspective, the WCST is widely regarded as a measure of executive functioning, particularly cognitive flexibility, rule shifting, and inhibitory control (Stuss & Levine, 2002). Increased error intensity during the task may reflect reduced adaptability in updating rules or maintaining goal-directed behaviour. The observed associations can therefore be interpreted within established theoretical frameworks of executive control. However, given the observational nature of the study, the results should be interpreted as associations rather than causal effects. The successful implementation of multi-event survival analysis in examining WCST performance opens avenues for further research in neuropsychology. It is important to acknowledge that the data were collected through an online experimental platform. As participation was voluntary and self-selected, the sample may not be fully representative of the broader population. Furthermore, variations in testing environments and external distractions could not be controlled. These factors may influence task performance and should be considered when interpreting the results. Although several socio-demographic variables, such as age, gender, and education level, were included in the models, other potential confounding factors, such as baseline cognitive ability or detailed socioeconomic indicators, were not explicitly measured. As the study is observational in nature, residual confounding cannot be ruled out. Future research incorporating broader cognitive and socioeconomic assessments may provide more comprehensive adjustment.

Other future works might explore phase-specific cognitive modelling, subtype-specific error analysis, Bayesian recurrent-event frameworks, or hybrid approaches integrating machine learning methods to better capture complex behavioural dynamics. Additionally, similar survival-based approaches may be extended to other psychological scales, such as the Hamilton Depression Rating Scale (HAM-D), by defining clinically meaningful events (e.g., remission or relapse) and modelling their occurrence over time. Such developments may contribute to more refined quantitative assessment tools in psychological and clinical research.

References

Abernathy K, Chandler LJ, Woodward JJ. Alcohol and the prefrontal cortex. Int Rev Neurobiol. 2010; 91: 289-320.

Al-Khalidi HR, Hong Y, Fleming TR, Therneau TM. Insights on the robust variance estimator under recurrent-events model. Biometrics. 2011; 67(4): 1564-1572.

Amorim LD, Cai J. Modelling recurrent events: a tutorial for analysis in epidemiology. Int J Epidemiol. 2015; 44(1): 324-333.

Andersen PK, Gill RD. Cox's regression model for counting processes: a large sample study. Ann Stat. 1982; 10(4): 1100-1120.

Anderson SW, Damasio H, Jones RD, Tranel D. Wisconsin card sorting test performance as a measure of frontal lobe damage. J Clin Exp Neuropsychol. 1991; 13(6): 909-922.

Balan TA, Putter H. A tutorial on frailty models. Stat Methods Med Res. 2020;29(11): 3424-354.

Cohen S, Kamarck T, Mermelstein R. A global measure of perceived stress. J Health Soc Behav. 1983; 24(4): 385-396.

Demakis GJ. A meta-analytic review of the sensitivity of the Wisconsin Card Sorting Test to frontal and lateralized frontal brain damage. Neuropsychology. 2003; 17(2): 255-264.

Dispenza J. You are the placebo: making your mind matter. Carlsbad (CA): Hay House; 2014.
Donaldson MG, Sobolev B, Kuramoto L, Cook WL, Khan KM, Janssen PA. Utility of the mean cumulative function in the analysis of fall events. J Gerontol A Biol Sci Med Sci. 2007; 62(4): 415-419.
Elahi C, Rocha TAH, Sakita F, Ndebea AS, Fuller A, Haglund MM, et al. An evaluation of traumatic brain injury patient outcomes at a referral hospital in Tanzania: evidence from a survival analysis. Neurosurg Focus. 2019; 47(5): E6. https://doi.org/10.3171/2019.8.FOCUS19515
Feldstein SN, Keller FR, Portman RE, Durham RL, Klebe KJ, Davis HP. A comparison of computerized and standard versions of the Wisconsin Card Sorting Test. Clin Neuropsychol. 1999; 13(3): 303-313.
Fortuny LA, Heaton RK. Standard versus computerized administration of the Wisconsin Card Sorting Test. Clin Neuropsychol. 1996; 10(4): 419-424.
Franz DJ. “Are psychological attributes quantitative?” is not an empirical question: conceptual confusions in the measurement debate. Theory Psychol. 2022; 32(1): 131-150.
Grant DA, Berg EA. A behavioral analysis of degree of reinforcement and ease of shifting to new responses in a Weigl-type card-sorting problem. J Exp Psychol. 1948; 38(4):404-411.
Greve KW, Bianchini KJ, Hartley SM, Adams D. The Wisconsin Card Sorting Test in stroke rehabilitation: factor structure and relationship to outcome. Arch Clin Neuropsychol. 1999; 14(6): 497-509.
Grimaldi P, Lau H, Basso MA. There are things that we know that we know, and there are things that we do not know we do not know: confidence in decision-making. Neurosci Biobehav Rev. 2015; 55: 88-97.
Heaton RK, PAR Staff. Wisconsin Card Sorting Test: computer version 4. Lutz (FL): Psychological Assessment Resources; 2003.
Heaton RK, Chelune GJ, Talley JL, Kay GG, Curtiss G. Wisconsin Card Sorting Test manual: revised and expanded. Odessa (FL): Psychological Assessment Resources; 1993.
Howard M, Gregertsen EC, Hindocha C, Serpell L. Impulsivity and compulsivity in anorexia and bulimia nervosa: a systematic review. Psychiatry Res. 2020; 293: 113354. https://doi.org/10.1016/j.psychres.2020.113354
Kleinbaum DG, Klein M. Survival analysis: a self-learning text. 3rd ed. New York: Springer; 2012.
Kohli A, Kaur M. Wisconsin Card Sorting Test: normative data and experience. Indian J Psychiatry. 2006; 48(3): 181-184.
Kolakowsky-Hayner SA. Wisconsin Card Sorting Test. In: Kreutzer JS, DeLuca J, Caplan B, editors. Encyclopedia of clinical neuropsychology. New York: Springer; 2011.
Kongs SK, Thompson LL, Iverson GL, Heaton RK. Wisconsin Card Sorting Test-64 card version: professional manual. Odessa (FL): Psychological Assessment Resources; 2000.
Kopp B, Lange F, Steinke A. The reliability of the Wisconsin card sorting test in clinical practice. Assessment. 2021; 28(1): 248-263.
Landau S. Using survival analysis in psychology. Underst Stat. 2002; 1(4): 233-270.
Landry O, Mitchell P. An examination of perseverative errors and cognitive flexibility in autism. PLoS One. 2021; 16(1): e0223160. https://doi.org/10.1371/journal.pone.0223160
Lange F, Brückner C, Knebel A, Seer C, Kopp B. Executive dysfunction in Parkinson’s disease: a meta-analysis on the Wisconsin Card Sorting Test literature. Neurosci Biobehav Rev. 2018; 93: 38-56.
Lawless JF, Nadeau C. Some simple robust methods for the analysis of recurrent events. Technometrics. 1995; 37(2): 158-168.

Li QH, Lagakos SW. Use of the Wei-Lin-Weissfeld method for the analysis of a recurring and a terminating event. Stat Med. 1997; 16(8): 925-940.

Loo J. Self-esteem [Internet]. The Decision Lab; 2021 [cited 2024 Sep 27]. Available from: https://thedecisionlab.com/reference-guide/philosophy/self-esteem

Lougheed JP, Benson L, Cole PM, Ram N. Multilevel survival analysis: studying the timing of children's recurring behaviors. Dev Psychol. 2019; 55(1): 53-65.

Maier H, Smith J. Psychological predictors of mortality in old age. J Gerontol B Psychol Sci Soc Sci. 1999; 54(1): P44-54.

Meng R, Li J, Wang Z, Zhang D, Liu B, Luo Y, et al. The Chinese version of the Perceived Stress Questionnaire: development and validation amongst medical students and workers. Health Qual Life Outcomes. 2020; 18(1): 70. https://doi.org/10.1186/s12955-020-01307-1

Nelson W. Graphical analysis of system repair data. J Qual Technol. 1988; 20(1): 24-35.

Ninomiya Y, Iwata T, Terai H, Miwa K. Effect of cognitive load and working memory capacity on the efficiency of discovering better alternatives: a survival analysis. Mem Cognit. 2024; 52(1): 115-131.

Oscar-Berman M, Marinkovic K. Alcoholism and the brain: an overview. Alcohol Res Health. 2003; 27(2): 125-33.

Ozga AK, Kieser M, Rauch G. A systematic comparison of recurrent event models for application to composite endpoints. BMC Med Res Methodol. 2018;18(1): 2. https://doi.org/10.1186/s12874-017-0462-x

Page MC. Survival analysis in psychology: effects of censoring and proportionality [dissertation]. Tempe (AZ): Arizona State University; 1998.

Pirau L, Lui F. Frontal lobe syndrome. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2023 [cited 2026 Sep 20]. Available from: https://www.ncbi.nlm.nih.gov/books/NBK532981

Prinja S, Gupta N, Verma R. Censoring in clinical trials: review of survival analysis techniques. Indian J Community Med. 2010; 35(2): 217-221.

PsyToolkit. Wisconsin Card Sorting Test (WCST) [Internet]. 2021 [cited 2024 Aug 28]. Available from: https://www.psytoolkit.org/experiment-library/wcst.html

Queensland Health. Brain map: frontal lobes [Internet]. Brisbane: Queensland Government; 2022 [cited 2026 Sep 20]. Available from: https://www.health.qld.gov.au/abios/asp/bfrontal

Rouault M, Fleming SM. Formation of global self-beliefs in the human brain. Proc Natl Acad Sci U S A. 2020; 117(44): 27268-27276.

Schwarzer R, Jerusalem M. Generalized self-efficacy scale. In: Weinman J, Wright S, Johnston M, editors. Measures in health psychology: a user's portfolio. Causal and control beliefs. Windsor (UK): NFER-Nelson; 1995. p. 35-37.

Sendic G. Frontal lobe [Internet]. Kenhub; 2023 [cited 2026 Sep 20]. Available from: https://www.kenhub.com/en/library/anatomy/frontal-lobe

Somsen RJM, Van der Molen MW, Jennings JR, van Beek B. Wisconsin Card Sorting in adolescents: analysis of performance, response times and heart rate. Acta Psychol (Amst). 2000; 104(2): 227-257.

Steinke A, Kopp B, Lange F. The Wisconsin Card Sorting Test: split-half reliability estimates for a self-administered computerized variant. Brain Sci. 2021;11(5): 529. https://doi.org/10.3390/brainsci11050529

Stoet G. PsyToolkit: a software package for programming psychological experiments using Linux. Behav Res Methods. 2010; 42(4): 1096-1104.

Stoet G. PsyToolkit: a novel web-based method for running online questionnaires and reaction-time experiments. Teach Psychol. 2017; 44(1): 24-31.

Stuss DT, Levine B. Adult clinical neuropsychology: lessons from studies of the frontal lobes. Annu Rev Psychol. 2002; 53: 401-433.

Stuss DT, Levine B, Alexander MP, Hong J, Palumbo C, Hamer L, et al. Wisconsin Card Sorting Test performance in patients with focal frontal and posterior brain damage: effects of lesion location and test structure on separable cognitive processes. Neuropsychologia. 2000; 38(4): 388-402.

Teubner-Rhodes S, Vaden KI Jr, Dubno JR, Eckert MA. Cognitive persistence: development and validation of a novel measure from the Wisconsin Card Sorting Test. Neuropsychologia. 2017; 102: 95-108.

Therneau TM, Grambsch PM. Modeling survival data: extending the Cox model. New York: Springer; 2000.

van Houwelingen HC, Putter H. Dynamic prediction in clinical survival analysis. Boca Raton (FL): CRC Press; 2012.

Wu W, Little TD. Quantitative research methods. In: Levesque RJR, editor. Encyclopedia of adolescence. New York: Springer; 2011.

Yin Y, Chou C. Multi-event survival analysis through dynamic multi-modal learning for ICU mortality prediction. Comput Methods Programs Biomed. 2023; 235: 107545. https://doi.org/10.1016/j.cmpb.2023.107545

Appendix I: The Perceived Stress Scale (PSS) and The General Self-Efficacy Scale (GSE)

The Perceived Stress Scale (PSS)

For each question, choose from the following alternatives (Cohen et al. 1983):

0. never, 1. almost never, 2. Sometimes, 3. fairly often, 4. very often

---

1. In the last month, how often have you been upset because of something that happened unexpectedly?
2. In the last month, how often have you felt that you were unable to control the important things in your life?
3. In the last month, how often have you felt nervous and "stressed"?
4*. In the last month, how often have you dealt successfully with irritating life hassles?
5*. In the last month, how often have you felt that you were effectively coping with important changes that were occurring in your life?
6*. In the last month, how often have you felt confident about your ability to handle your personal problems?
7*. In the last month, how often have you felt that things were going your way?
8. In the last month, how often have you found that you could not cope with all the things that you had to do?
9*. In the last month, how often have you been able to control irritations in your life?
10*. In the last month, how often have you felt that you were on top of things?
11. In the last month, how often have you been angered because of things that happened that were outside of your control?
12. In the last month, how often have you found yourself thinking about things that you have to accomplish?
13*. In the last month, how often have you been able to control the way you spend your time?

14. In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?

---

*Scored in the reverse direction

The Perceived Stress Scale (PSS) consists of 14 items, each rated on a 0–4 scale, with a total possible score ranging from 0 to 56. Higher scoring reflected higher levels of perceived stress (Meng et al., 2020). This score is divided into seven equal categories to assess stress levels in this study.

- 1 = Very Low: (0–8 points)
- 2 = Low: (8-16 points)
- 3 = Below Average: (16-24 points)
- 4 = Average: (24-32 points)
- 5 = Above Average: (32-40 points)
- 6 = High: (40-48 points)
- 7 = Very High: (48-56 points)

The General Self-Efficacy Scale (GSE)

For each question, choose from the following alternatives (Schwarzer and Jerusalem, 1995):
1. Not at all true
2. Hardly true
3. Moderately true
4. Exactly true

---

1. I can always manage to solve difficult problems if I try hard enough
2. If someone opposes me, I can find the means and ways to get what I want.
3. It is easy for me to stick to my aims and accomplish my goals.
4. I am confident that I could deal efficiently with unexpected events.
5. Thanks to my resourcefulness, I know how to handle unforeseen situations.
6. I can solve most problems if I invest the necessary effort.
7. I can remain calm when facing difficulties because I can rely on my coping abilities.
8. When I am confronted with a problem, I can usually find several solutions.
9. If I am in trouble, I can usually think of a solution
10. I can usually handle whatever comes my way.

The General Self-Efficacy Scale (GSE) consists of 10 items scored on a 1–4 scale, with a total score ranging from 10 to 40. This range is also divided into seven equal categories:

- 1 = Very Low: (10–14.3 points)
- 2 = Low: (14.4–18.6 points)
- 3 = Below Average: (18.7–22.9 points)
- 4 = Average: (23–27.1 points)
- 5 = Above Average: (27.2–31.4 points)
- 6 = High: (31.5–35.7 points)
- 7 = Very High: (35.8–40 points)

These categorised scores were used to analyse the relationship between participants' perceived stress, self-belief, and performance in WCST during the study.