# Assessment Technical Manual

## Literature review

The purpose of this literature review is to identify the competencies important for c-suite success private-equity funded firms to confirm the preliminary theoretical model developed through job analysis by subject matter experts. Within the literature, private equity company success is typically defined as the firm having exited the investment successfully or being reasonably on track to do so (Pratch & Jacobowitz, 2004).

**Leadership Ability**

While being able to innovate and take risks to enable growth or cope with stress is important for success, these abilities alone are not sufficient without the ability to lead a team and gain buy-in. In particular, successful leaders in PE-funded ventures have high standards for their subordinates and motivate them to achieve their ***vision*** for the company, even if they privately lack confidence in the ability of subordinates to perform at the required level (Pratch & Jacobowitz, 2004). Indeed, leaders of PE-funded firms must have enough self-***confidence*** to make final decisions across contexts without relying on others for validation or being concerned about others’ abilities (Pratch, 2001) and must have sufficient ***authority*** to take charge of situations and control and direct others.

**Collaboration**

Given that leaders of private-equity funded firms have only the board of directors as their superiors, leaders must be directly able to ***influence*** their employees and get buy-in for decisions. Without this ability, leaders can be vulnerable to conflict avoidance and manipulation (Pratch, 2001). On the other hand, leaders that can influence their subordinates are better able to motivate their workforce, foster collaboration and commitment, and support a more adaptive approach (Pratch, 2001). However, despite a need to take charge, it is important that leaders in PE-funded businesses also have adequate levels of ***integrity*** to maintain social relationships and support negotiation by demonstrating their trustworthiness and ability to understand the needs and perspectives ofothers, promoting cooperation (Odgers Berndtson, 2021; Pratch, 2001).

**Finding solutions**

While in publicly traded companies, much of the focus of leaders is on governance, risk, and compliance to preserve reputation and consequently dealing with more bureaucracy, leaders in PE funded enterprises place more emphasis on value creation to scale the business and place it in an attractive position to be acquired (Acharya et al., 2009; RHR International, 2021). Given the limited resources available in PE funded ventures (Acharya et al., 2009; Pratch & Jacobowitz, 2004; RHR International, 2021), leaders must be creative in their approach to adding value and must intensely gather information to inform their decisions (Acharya et al., 2009). Indeed, leaders who are high in openness and consequently higher in ***ideation,*** generate more novel and innovative ideas and are therefore more adaptable. This, along with greater ***opportunism***, or the tendency to be more entrepreneurial and recognise and take opportunities, can increase the market value of the firm (O’Reilly et al., 2014).

**Execution at speed**

Once solutions to problems have been identified, it is vital that leaders of PE-funded firms take swift action, particularly given the dynamic landscape. This requires leaders to persevere and be decisive such as to not miss out on first-mover advantage. As such, leaders in these companies must have an appropriate risk propensity to be comfortable with taking calculated risks (RHR International, 2021; Schneider & Lang, 2013). Indeed, PE-funded companies must be fast moving and dynamic to take advantage of emerging consumer demands; moving too slowly could see companies miss out, so leaders must also be ***driven*** to take action, particularly in stressful situations to ensure that opportunities are not missed and must have the self-***discipline*** to follow through with their actions once they have committed to a plan (Pratch, 2001). However, when outcomes are not as expected or interpersonal conflict does occur, it is important that leaders of PE funded ventures are ***resilient*** and able to bounce back to correct actions and deal with stress (Pratch, 2001; Pratch & Jacobowitz, 2004).

**Motivators**

Given the dynamic nature of PE-funded firms, leaders must be motivated by ***adventure*** so that they can try new things without fear of failure and more concerned with managing risks over avoiding risks (Acharya et al., 2009) and are not concerned with conformityto norms or traditions. Moreover, successful leaders of PE-funded companies derive significant satisfaction from achievement (Pratch & Jacobowitz, 2004) and are therefore motivated by the impact or ***purpose*** of their work, as well as the ***reward*** that may lie at the end. This also requires motivation to ***master*** skills and face new challenges to move forward with an appropriate level of expertise (Pratch, 2001).

Given the seniority of leaders of PE-funded firms and the relative lack of oversight, leaders can also be motivated by the ***power*** this gives them, in that they are able to override decisions made from other executives and have final decision-making powers (Pratch, 2001). To allow them to make these final decisions, leaders must also be motivated by opportunities for ***ownership*** and such decision-making, where they are accountable for the firm’s outcomes and direction. On the other hand, being able to maintain social connections and share ***connections*** with others in the firm contributes to success, particularly when leaders are motivated and able to understand the needs and wants of senior executives, both internally and externally (Pratch, 2001).

Failure of leaders to be resilient and able to cope with stress can jeopardise the success of the venture. In particular, the most successful leaders demonstrate ***active coping***, where stress fuels determination instead of causing them to retreat or pause and can lead to stronger leadership performance across time and situations (Pratch & Jacobowitz, 2004). Central to this ability is the ***need for achievement***, where leaders that demonstrate active coping strive to achieve both personal and professional goals even in the face of adversity (Pratch, 2001). Indeed, and are therefore high in ***hedonism***. Active coping is also driven by ***emotional stability***, where leaders that are unable to cope with stress and uncertainty can become paralysed and fail to take any action (Pratch & Jacobowitz, 2004), meaning that they lack the active coping abilities needed to drive the company forward.

**Derailers/inhibitors**

Although it is important that leaders in PE funded companies are agile and driven to achieve, being overly ***dominant*** can overwhelm subordinates and limit their ability to execute and can result in passive coping, or withdrawal (Pratch, 2001). Being overly dominant can also disrupt interpersonal relationships within the organisation (Kalma et al., 1993) and could result in tensions with the board, where positive relationships between the board and executives supports venture success (Pratch & Jacobowitz, 2004).

Furthermore, leaders that are too comfortable with risk and do not stop to consider the consequences of their actions can become ***reckless*** and take away from the benefits of having some baseline procedures and routine (Pratch, 2001). Moreover, being too ready to take on opportunities without having an adequate action plan can lead to ***mercurial*** leaders that are unpredictable and volatile, which can impact social relationships, with successful leaders of PE-funded ventures coming from stable backgrounds (Pratch & Jacobowitz, 2004). Furthermore, excessive self-confidence or ***hubris*** can also result in conflicts with the board, whereby executives resist recommendations or drag their feet in implementing recommendations if they perceived that only they know what is best for the company, which can result in a lack of growth strategy and hinder success (Pratch, 2001). Indeed, Moreover, powerstruggles within the organisation can hinder growth if leadership are not willing to delegate or respect decisions made by others that are within the scope of their role (Pratch, 2001).

**Conclusion**

Overall, the literature supports four competencies that are important for leadership success in PE-funded ventures: leadership ability, collaboration, ability to execute at speed, and ability to find solutions. Successful leaders are also motivated by a sense of adventure, the purpose of their work, and the opportunity for reward for their success. They are also motivated by the power and ownership that their role gives them, and the opportunity to master their skills and connect with others to influence importance outcomes. However, too high levels of these traits can lead to hubris, Machiavellian, dominant, recklessness, or mercurial leaders, so there must be a balance between traits to ensure that opportunities can be realised, action plans executed, and the firm led in the necessary direction without disruption to social relationships or taking unnecessary risks.

## Theoretical model

Based on the literature review, the final theoretical model has three key dimensions – namely personality, red flags, and motivators – made up of 23 traits, where the personality dimension is made up of four factors: leadership, collaboration, execution at speed, and innovation. The model structure has also been validated using a panel of senior leaders in organisations around the world.

Within the personality domain, there are four factors: leadership ability, collaboration, executing at speed, and finding solutions. Leadership ability has three traits:

* Authority – Takes charge of situations; controls and directs
* Vision – Sees the ‘big picture’ and maintains line of sight
* Confidence – Self-belief and assurance in oneself and decision-making ability across domains

The collaboration factor has two traits:

* Influence – Can affect how others think and feel without control or direction
* Integrity – Genuine, honest and straightforward. Authentic

The executing at speed factor has four traits:

* Drive – Strong desire to accomplish goals; propensity to act decisively andget things done
* Discipline – Planned rather than spontaneous behaviour; attention to detail and accuracy; organises and plans to achieve goals
* Agility -- – Switches easily between different cognitive processes; comfortable with ill-defined problems and situations; adaptable and constructive
* Resilience – Remains calm and optimistic under pressure; persists in the face of adversity; recovers from setbacks

The finding solutions factor has two traits:

* Ideation – Generates original and/or innovative ideas; makes unexpected connections
* Opportunism - Alert to opportunity; prepared to seize opportunities

Within the red flag domain, there are five key traits:

* Narcissism/Hubris – Conceit and self-importance; overestimation of knowledge and/or ability in respect of tasks; misplaced belief in unique and exceptional abilities
* Mercurial – Given to sudden changes of mood, behaviour or direction; Given to unconventional or strange behaviour or beliefs; Difficult to predict and/or surprising
* Machiavellianism – Deliberate deceitfulness in the pursuit of one’s interest; acting in bad faith; Ruthless pursuit of own interests regardless of considerations of right or wrong; General distrust of the motives of others; attribution of bad faith
* Reckless – Fails to stop and think. Acts without forethought and sufficient regard for consequences
* Dominant – Forceful, insistent, domineering; Hostile and argumentative; Unyielding in the face of evidence or argument

Within the motivation domain, there are seven key motivators for leaders of private-equity funded firms:

* Adventure – Experiencing the rush from taking on a challenge or doing something risky
* Connection – Trusting and respecting others. Sharing viewpoints and goals with colleagues.
* Mastery – Continuous growth and self-improvement to overcome challenges and build expertise
* Ownership – Having freedom, autonomy, and agency in day-to-day tasks and decision making
* Power – Having influence and control over others’ actions, views, and behaviours
* Purpose – Having a noticeable impact and making a difference. Doing something good or worthwhile
* Reward – Material and non-material affirmation of efforts, expertise and outputs

The structure of this model was confirmed with principal component analysis (PCA) and subsequently confirmatory factor analysis.

## Mapping to the Big Five

The Big Five personality traits are an overarching personality system into which all traits can be classified. It offers a useful point of comparison and common language to compare traits and models, and to connect local models to the research literature. The theoretical model for the Napoleon-Bain assessment can be mapped to the Big Five personality traits, with conscientiousness particularly well represented as the most consistent predictor of job performance across occupations (Barrick & Mount, 1991; Sackett et al., 2022; Schmidt et al., 2016; Schmidt & Hunter, 1998).

Conscientiousness maps onto confidence, drive, discipline, and integrity. Emotional stability maps onto agility and resilience, extraversion onto authority and influence, and openness to experience onto vision, ideation, and opportunism.

# Image bank creation

The assessment uses a forced-choice format, whereby test-takers are presented with pairs of images and are asked to indicate which image in the pair represents them best. Each pair of images represent different traits from the theoretical model, and are both either desirable traits or undesirable traits. Assessments of this format can prevent central tendency and extreme response styles (Brown & Maydeu-Olivares, 2013)  since there is no midpoint, as well as acquiescence responding, where respondents select both positive and negative statements, since they are not able to endorse all of the statements presented to them (Brown & Maydeu-Olivares, 2013). Further, they are more resistant to faking than traditional measures (Salgado & Táuriz, 2014) since it is more difficult for test-takers to choose answers that they believe will lead to them being viewed more favourably, which is particularly important in high-stakes contexts like talent management and acquisition.

Items for the assessment were created by subject matter experts to represent the theoretical model. Short statements are also included to support interpretation. The forced-choice pairs represented either two positive sentiments or two negative sentiments such that neither option should be more desirable than the other, giving a truer representation of test-takers instead of being influenced by attempting to choose responses that may be deemed more desirable.

In total, 80 image pairs were created for personality/red flags, and 41 for motivation, totalling 101 questions consisting of 202 images. Accordingly, each personality trait/red flag was presented by 10 images and each motivator by six images.

# Scoring algorithm creation

The assessment is scored using a machine learning based regression approach, where the models are trained to predict personality and motivation scores as measured by validated, questionnaire-based scales using image choices. A machine learning based approach was selected since a summative approach to forced-choice formats, where the number of images designed to measure a certain trait that are selected are summed to get the score for that trait, leads to ipsative scores. This is where everyone receives the same total score across all traits, calculated by adding up the score for each trait, since there is only a finite number of “points” available across all traits (Brown & Maydeu-Olivares, 2013). Methods have been proposed to overcome this based on item response theory (IRT) (Brown & Maydeu-Olivares, 2011, 2013), however, they require specialist implementation and have strict requirements for questionnaire factor structure. Machine learning based approaches, on the other hand, have been demonstrated to perform well with forced-choice image-based assessments of personality (Hilliard et al., 2022b, 2022a) and do not require specialist software or macros to create or run (e.g., Mplus) since they can be directly created in Python. The machine learning based approach also uses a data-driven approach, where the weights of predictors are determined based on patterns in the data, rather than potentially incorrect assumptions about what each item measures. This can vary from the trait that they are designed to measure since images can be more open to interpretation (Hilliard et al., 2022a). Moreover, more datapoints can be used to predict scores since all images (predictors) can be included in the model, which may provide additional insights due to personality traits naturally overlapping.

## Panel data

Models were trained on a dataset that represented global leaders across various industries. The data represents a range of races/ethnicities and nationalities, and includes neurodivergent individuals and individuals with health condition to maximise the representativeness of the data and ensure the algorithm is optimised for different subgroups and ways of thinking.

During the panels, participants were asked to complete the questionnaire-based outcome scales and image-based assessment, as well as self-report their success in their role over the past year.

## Scoring algorithms

The assessment is scored using a machine learning based approach called Ridge regression using image choices to predict scores. Ridge regression has a regularisation parameter that shrinks coefficients in a way that is proportional to their size based on the sum of the squared coefficients, where larger coefficients have greater shrinkage (McNeish, 2015). This can help to make the model more generalisable to other unseen datasets by reducing overfitting. Moreover, Ridge regression is better able to handle collinear predictors, or predictors that correlate highly (McNeish, 2015). This is beneficial for personality assessments where predictors, or image choices, are expected to correlate since respondents will consistently select images that represent their personality traits.

To determine the most appropriate hyperparameters for the models and maximise the generalisability, 10-fold cross validation was used. The models were trained on 70% of the data, with the remaining 30% acting as an unseen sample that could be used to examine the generalisability of the models beyond the training dataset (Jacobucci et al., 2016).

Overall, the models perform well in terms of convergent validity and the performance is generalisable beyond the training data, as determined by the test set correlations. Models also generally demonstrate good discriminant validity, which measures the extent to which an assessment of one construct measures a different construct, where an assessment of one construct should not be strongly related to another construct if the two constructs are theoretically distinct (Hughes, 2017). When creating new assessment measures, a common way to establish the convergent and discriminant validity of the assessment is through the multitrait-multimethod approach, which involves correlating scores of two or more traits across two or more methods of measurement (Campbell & Fiske, 1959). In the case of Napoleon-Bain image-based assessment, this is represented by correlating the scores predicted by the scoring algorithms with scores on the questionnaire-based measures. While there is not a specific threshold for determining whether a measure has discriminant validity, heterotrait-hetero-method correlations should not be as high as convergent validity (Campbell & Fiske, 1959). The personality scores generated by the scoring algorithms also correlated well with self-reported success and have similar predictive validity compared to meta-analytic estimates of the predictive validity of personality traits.

Adverse impact refers to differences in selection rates for different subgroups based on characteristics such as sex/gender and race/ethnicity caused by differences in scores (De Corte et al., 2007). To examine the potential for adverse impact, subgroup scores differnces in scores based on age (binarised into below/above 40 in line with the Age Discrimination in Employment Act), sex/gender, race/ethnicity, presence of a learning difference, and presence of a health condition were examined using three widely used metrics:

* **Four-fifths rule** – compares the pass rates of subgroups to the group with the highest rate to calculate an impact ratio, where ratios below .80 can indicate adverse impact (Equal Employment Opportunity Commission, 1978)
* **Two standard deviations rule** (also known as the z-test) – compares the expected and observed pass rates of each group based on the proportion of data that each subgroup represents, where values >2 indicate that there is a statistically significant discrepancy in expected and observed pass rates (Morgan, 2010; Morris & Lobsenz, 2000)
* **Cohen’s *d*** – a measure of effect size of the difference between means, where values above .20, .50, and .80 indicate small, medium, and large effect sizes, respectively (Cohen, 1992). The current study used a threshold of +/-.30 as indicative of group differences.

Patterns of differences in subgroup scores mirrored the pattern that was observed in the training data, meaning that these group differences were not caused by the assessment itself or the scoring algorithms and were likely to be genuine differences in personality.

# Accessibility and diversity

The assessment was developed with accessibility and diversity in mind from the very initial design phase. As such, the images in the assessment deliberately represent a range of ethnicities, races, genders, and ages and avoid stereotyped behaviours, maximising representation. Images are also supported by short statements to aid interpretation and reduce ambiguity. Furthermore, image interpretations are not reliant on colour so they do not pose a barrier for colour blind individuals, and the short statements support applicants who rely on a screen reader to maximise accessibility for visually impaired test-takers.

Moreover, when collecting the validation data, specific panels were run to collect responses for neurodivergent respondents, as well as those impacted by long-term health conditions, in order to ensure that the algorithms are optimised for a variety of thinking styles. Our research indicates that image-based formats can be beneficial for neurodivergent test-takers by reducing cognitive burden, improving engagement, and eliciting greater focus:

* Dyslexia - image-based formats are more fun and help to focus attention on the assessment compared to questionnaire-based formats. Including humorous images helps to maintain motivation, and including a couple of keywords with images helps with ambiguity in interpretation while not being too text-heavy.
* ADHD - images make the assessment more engaging and easier to focus on and reduce the likelihood of being distracted compared to traditional formats
* Autism - the test was “awesome and fun to take”. The combination of images with keywords to support interpretation is the “perfect combo” and the use of contextualised images helps with understanding compared to contextually-agnostic statements

# AI-Powered Chatbot: Coach

The AI-powered Coach can be used to aid the interpretation of test-taker reports, provide summaries, and answer questions about the assessment itself. As with all large language models, outputs should be sense-checked and used to support, rather than make, decisions.

## Chatbot Finetuning

The current version of the AI-powered Coach relies on a Retrieval-Augmented Generation (RAG) system, which utilizes prompt engineering with GPT-4 Turbo and an external knowledge base incorporating valuable literature to enhance response accuracy and relevance.

To establish a robust system for future improvement based on user feedback on the summaries or conversations generated by the Coach, and to ensure that this feedback is effectively utilized for finetuning the model or adjusting prompts, a number of important factors have been kept in mind in order to develop a responsible and effective AI 'Coach':

* **Training Data Set:** Coach will be improved using user-generated feedback on the summaries and conversations provided by the AI Coach. This data can include ratings, qualitative feedback, and specific annotations indicating whether the content was helpful, accurate, and unbiased.
* **Data Gathering:** This feedback data is gathered directly within the application interface, where users are prompted to rate the helpfulness and accuracy of the AI-generated content immediately after receiving it, with mechanisms for reporting biases, inaccuracies, or other concerns.

* **Data Labelling:** initial labels on the user-inputted feedback data are semi-automated.For more nuanced feedback, a manual review by a team of trained annotators categorizes feedback into more detailed labels, such as types of bias, areas of inaccuracy, or aspects of helpfulness.
* **Training rules:** the Coach language model is trained with the objective of maximising the efficacy, helpfulness, and unbiased nature of the content it generates. Training rules include prioritising user engagement metrics (e.g., positive ratings), minimising identified biases, and enhancing the diversity of perspectives in responses. Moreover, techniques like reinforcement learning from human feedback (RLHF) all the model to learn directly from user ratings and annotations to improve over time.

## AI ethics

**Improving Coach with user feedback**

To establish a system for future improvement based on user feedback on the summaries or conversations generated by the Coach large language model (LLM), and to ensure that this feedback is effectively utilized for finetuning the LLM or adjusting prompts, a number of important factors have been kept in mind in order to develop a responsible and effective AI 'Coach':

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* **Data Gathering:** This feedback data is gathered directly within the application interface, where users are prompted to rate the helpfulness and accuracy of the AI-generated content immediately after receiving it. Additionally, mechanisms for reporting biases, inaccuracies, or other concerns could be integrated.

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**Auditing for adverse impact**

In addition, conducting regular audits of the AI's performance across a variety of demographic groups and topics is crucial for identifying any adverse impacts. These audits include benchmarking analyses to uncover systematic biases or disparities in the modelss performance, utilizing tools such as BBQ or BOLD for bias benchmarking, Toxigen for toxicity benchmarking, Halueval, and Truthful QA for hallucination benchmarking. Additionally, Red Teaming Tests are used to evaluate the model's robustness and security. These include:

* Static Red Teaming: Employing publicly available red teaming datasets, such as Harmful QA, Cat QA, Adversarial QA, etc., to assess the model's robustness and security against biased, harmful, and sensitive elicitation questions.
* Dynamic Red Teaming: Leveraging LLM to generate a private red teaming dataset that dynamically tests the model's robustness and security, offering a continuous evaluation approach.
* Interactive Red Teaming: Engaging in agent interaction to allow other LLMs to persuade or deceive our model into producing harmful or stereotypical content. This method tests the model's conversational integrity at the interaction level.

Moreover, qualitative engagement with external experts or diverse focus groups is used to uncover subtle biases or unintended consequences not immediately evident from the testing described above.

**Increasing Diversity**

To increase diversity and mitigate bias, the data collection and training process explicitly incorporates diverse perspectives. This involves ensuring that the feedback and training data come from a broad and diverse user base and that the data labelling and review processes involve individuals from varied backgrounds. Indeed, the development team alone includes individuals with various areas of expertise, including business psychology, AI ethics, and machine learning, and represents a variety of nationalities. Techniques such as counterfactual data augmentation, where the training data is augmented with examples that challenge stereotypical associations or biases, are also employed to increase diversity.

**Mitigating Unintended Consequences and Bias**

Continuous monitoring and feedback loops are crucial. This involves not only adjusting the model based on user feedback but also regularly re-evaluating the criteria for feedback collection and the model's training objectives. As such, ethical guidelines and frameworks guide the development process, ensuring that decisions around data use, model training, and performance evaluation prioritize fairness, transparency, and accountability.

In summary, a feedback loop for finetuning the AI 'Coach' based on user feedback involves careful consideration of data collection, labeling, and training processes. Assessing for adverse impact and actively working to increase diversity and mitigate bias are crucial components of responsibly deploying AI in this context. Engaging with diverse stakeholders and continuously monitoring the system's impact is key to understanding and addressing unintended consequences.

# Q&A

**How were my scores calculated?**

Scores are calculated based on image choices, where each image is designed to represent a certain trait that is useful for predicting success in leaders of private equity funded firms. A machine learning based, data-driven approach is used to determine the importance of each image for each trait and therefore what its weight is when calculating your score for each trait.

**How do you know these traits matter?**

The traits measured in this assessment are those that are most important for the success of leaders of private-equity funded firms. These traits were identified through job analysis by subject matter experts, where we looked at the key responsibilities of leaders in these firms and the traits needed to meet these responsibilities. Once we had our initial model, we then conducted a literature review to make sure our hypotheses were supported, and also validated the model with panel data that represents global leaders.

**I don’t think my results describe me well**

The scoring of this assessment uses a data-driven approach, so it may have uncovered patterns that you might not even be able to identify in yourself. The tool has been validated to make sure that it measures personality in a similar way to other assessment format and that it gives you accurate results.

Although personality is relatively stable, your responses might also have been influenced by factors such as your mood or where you took the assessment (i.e., at home, at work, during your commute). This assessment is also used as part of a suite of tools and evaluation methods, all of which may capture different insights about you and will create a richer profile.

**Who am I being compared against?**

Scores for each trait have been benchmarked based on a dataset of global leaders across multiple leadership positions. This dataset represents individuals with a number of years of experience in their positions and a range of nationalities and ethnicities, including neurodivergent individuals and those suffering from long-term health conditions. In short, you are being compared against data that represents a diverse range of individuals that are in a similar position to you.

**Do these scores matter in real life?**

Yes – the theoretical model underlying the tool was developed by looking at the traits that are most important for the success of leaders of private equity funded firms. We also made sure that the scores outputted by the assessment were related to performance by asking global leaders who took the assessment during the validation to report their success and looking at how this related to their personality scores.

**I wanted to choose both images a lot of the time, does this mean my results are inaccurate?**

The assessment uses what is known as a forced-choice format, where you are forced to choose between responses. Remember, the assessment asked which image you related to *most*, even if you thought that both images represented you. Forced-choice formats make you think about your response and reflect, so that it is harder to rush through without thinking. This results in better quality data that will provide more useful insights about you, and results in a truer representation of you since the format is more robust to influences from what you might think the more desirable answer, as is common with other formats.