# A brief report on the 'Spotlight' personality tool

By Dr. Chin Wei Ong

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Since its launch in early-2018, the 'Spotlight' personality tool has been used by diverse groups of people hailing from organisations across various industries. The opportunities to apply 'Spotlight' during this time have provided us with useful feedback on the actual reports, and a significant amount of data to explore further validation processes. As a follow-up to the initial exploratory analysis of 'Spotlight' (see White Paper; Ong, 2018), this brief report aims to provide further statistical analysis to determine the support for the FLEX and COPE models, using the data collected since this time.

## 1. Descriptive statistics and participant information.

All the analyses presented in this brief report is based on a sample of 1398 (785 men, 569 women, 44 unknown) participants who completed the English version of Spotlight 2.0. Descriptive statistics for the FLEX and COPE variables can be found in Table 1. Further, we did not detect any outliers after inspecting skewness, kurtosis and Mahalanobis distance statistics across all variables, thus retaining all data for analyses.

| | Mean | Standard deviation | Minimum | Maximum | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| **Forceful** | 2.62 | 1.54 | 0.00 | 6.00 | 0.26 | -0.93 |
| **Logical** | 3.36 | 1.60 | 0.20 | 6.00 | -0.17 | -1.05 |
| **Empathic** | 3.87 | 1.41 | 0.00 | 6.00 | -0.69 | -0.30 |
| **eXpressive** | 3.54 | 1.35 | 0.00 | 6.00 | -0.19 | -0.77 |
| **Contained** | 3.12 | 1.30 | 0.00 | 6.00 | -0.11 | -0.79 |
| **Optimistic** | 2.46 | 1.62 | 0.00 | 6.00 | 0.37 | -0.96 |
| **Prudent** | 3.46 | 1.20 | 0.00 | 6.00 | -0.32 | -0.60 |
| **Engaged** | 4.15 | 0.94 | 0.00 | 6.00 | -0.54 | 0.11 |

*Table 1: Mean scores, Standard deviations, Minimum scores, Maximum scores, Skewness and Kurtosis statistics for FLEX and COPE.*

## 2. Construct/factorial validity of FLEX and COPE

The FLEX and COPE models in 'Spotlight' are both conceptualised as four-factor models. Although it is possible to be guided by these theorised four-factor structures when we analyse the factor structures of FLEX and COPE, , we decided on an exploratory approach (i.e., not specifying and confining the data to a set factor structure) in the initial analysis of 'Spotlight' (Ong, 2018) because it was the first time we tested the factor structure of the models. This data-driven approach allowed us to see if a similar factor structure was reflected in the data, which was indeed the case. With the four-factor structures of FLEX and COPE established, we are able to conduct factor analyses that are confirmatory in approach. To find out if the data collected since the time of this first report fits within the specified four-factor structure, we conducted Bayesian Structural Equation Modeling (BSEM) for all 10 sets of items in both FLEX and COPE.

### Why Bayesian?

In order to decide whether a psychological observation belongs to a group comprising other hypothetically similar observations, the traditional approach (i.e., maximum likelihood) to factor analysis typically confines psychological observations to a hypothesised group of observations (i.e., a factor or latent variable), not allowing them to associate with other groups of observations. If this observation does not fit with its hypothesised group, it will often be deleted from the group. While this has made it straightforward to judge whether an observation belongs to their intended group, the reality is that the psychology of human beings (and, in fact, most phenomena) is often intertwined, fluid and complex. Such a constrained approach limits the applicability of research findings, as it is a restricted model of reality. A Bayesian[1] approach to factorial analysis (BSEM) is gaining popularity in research, because it liberates the analysis from the constraints applied in more traditional approaches. This increased flexibility to allow psychological observations to freely associate with other observations and factors allows for a more accurate reflection of reality. A Bayesian approach also means that observations are less likely to be deleted due to its supposed lack of 'fit', thereby preserving the hypothesised integrity of the factors and their intended meanings/definitions. Finally, adopting BSEM enables us to handle relatively smaller sample sizes and data that are highly skewed. This is because, unlike the traditional approach, Bayesian theory does not rely on assumptions of normality or large sample theory (Lee & Song, 2004; Muthén & Asparouhov, 2012).

BSEM for each of the FLEX and COPE models were conducted in three steps – with model flexibility increasing with each step. As a starting point, the conditions specified in step one essentially replicate that of the more traditional maximum likelihood approach – factors and observations are not allowed to freely associate with one another outside of their intended grouping. In step two, we allowed the factors and observations to freely associate with one another. In step three, we allowed the factors, observations and the residuals (proportions of variance that are unexplained by the model) to freely associate with one another. If the factors, observations and residuals in steps two and three associate with one another, these associations should be small in magnitude relative to the hypothesised associations, unless informed by findings of prior research. To specify these small associations in the model, informative priors for standardised data were set at zero with a variance of ±0.01, which make small associations possible at the 95% credible interval with limits of ±0.20 (Muthén & Asparouhov, 2012).

Both the FLEX and COPE models were estimated with the Markov Chain Monte Carlo (MCMC) algorithm with the Gibbs sampler and two chains. We conducted the models initially with 100,000 iterations, and later with 200,000 iterations to ensure convergence and stability of the estimates. Model convergence was determined by a potential scale reduction factor (PSRF) of between <1.2 (Brooks & Gelman, 1997). Model fit was determined with the Posterior Predictive P-value (PPP) and its associated credibility intervals (CIs). A PPP value greater than 0.05 and CIs that incorporated zero demonstrated acceptable model fit, while a PPP value close to 0.50 and CIs that centred on zero demonstrated excellent model fit. For the intended associations to be deemed acceptable, factor loadings should be greater than 0.40 (Ford, MacCallum, & Tait, 1986), while cross-loadings and residual correlations should have credibility intervals encompassing zero (i.e., within their pre-specified boundaries; Muthén & Asparouhov, 2012).

According to the model fit indices, both the FLEX and COPE models reached convergence at 88,700 and 86,900 iterations respectively. Both

[1] To learn more about the Bayesian approach to statistics, the following is a good place to start: https://alexanderetz.com/2016/02/07/understanding-bayes-how-to-become-a-bayesian-in-eight-easy-steps/

models attained excellent model fit in step 3. For FLEX, the PPP value was 0.51 and CI (-118.02, 113.091) centering around zero. For COPE, the PPP value was 0.53 and CI (-121.80, 112.50) centering around zero. Further, the overall factor loadings for FLEX and COPE suggest that the items are capturing responses that are intended for their intended factor – confirming the four-factor structure for FLEX and COPE. For FLEX, all factor loadings were statistically significant and above the recommended 0.40 value (see Table 2 for the range of factor loadings). For COPE, all the factor loadings were statistically significant, and with the exception of five items (p1, en1, en2, en4 and en6), all the factor loadings were above the recommended 0.40 value (see Table 3 for the range of factor loadings). The factor loadings for these five items deviated very modestly from the recommended value, and were consequently retained in the COPE model.

| | Average and range of factor loadings | | | |
|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **Factor 3** | **Factor 4** |
| **Forceful** | **0.64**<br>**0.53 – 0.70*** | 0.00<br>0.08 – 0.09 | -0.01<br>-0.07 – 0.05 | 0.00<br>-0.11 – 0.09 |
| **Logical** | 0.00<br>-0.06 – 0.08 | **0.68**<br>**0.42 – 0.82*** | 0.00<br>-0.07 – 0.04 | -0.02<br>-0.13 – 0.03 |
| **Empathic** | -0.01<br>-0.09 – 0.07 | -0.01<br>-0.09 – 0.13 | **0.66**<br>**0.44 – 0.78*** | 0.00<br>-0.10 – 0.07 |
| **eXpressive** | -0.01<br>-0.09 – 0.08 | -0.02<br>-0.09 – 0.06 | -0.01<br>-0.09 – 0.07 | **0.61**<br>**0.54 – 0.74*** |

*Table 2: Average and range of factor loadings for FLEX four-factor model. * denotes p<.01.*

| | Average and range of factor loadings | | | |
|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **Factor 3** | **Factor 4** |
| **Contained** | **0.56**<br>**0.45 – 0.67*** | -0.01<br>-0.03 – 0.07 | 0.00<br>-0.09 – 0.07 | -0.01<br>-0.04 – 0.03 |
| **Optimistic** | -0.01<br>-0.05 – 0.05 | **0.66**<br>**0.51 – 0.80*** | -0.01<br>-0.06 – 0.03 | -0.01<br>-0.08 – 0.05 |
| **Prudent** | 0.00<br>-0.05 – 0.06 | -0.01<br>-0.09 – 0.04 | **0.53**<br>**0.38 – 0.62*** | 0.00<br>-0.07 – 0.05 |
| **Engaged** | -0.01<br>-0.08 – 0.06 | 0.00<br>-0.08 – 0.10 | 0.00<br>-0.12 – 0.08 | **0.45**<br>**0.36 – 0.54*** |

*Table 6: Average and range of factor loadings for COPE four-factor model. * denotes p<.01.*

## 3. Reliability

Cronbach's Alpha is a popular measure of internal consistency and is a commonly used to determine scale reliability. A Cronbach's Alpha coefficient of 0.70 or higher is typically considered "acceptable" in scale development. The Cronbach's Alpha coefficients for FLEX and COPE factors are either higher or very close to the commonly accepted 0.70 value (Table 4 and 5), which suggests that the items measuring FLEX and COPE are considered to be reliable.

| | Forceful | Logical | Empathic | eXpressive |
|---|---|---|---|---|
| Overall | 0.87 | 0.89 | 0.88 | 0.84 |

*Table 7: Cronbach's Alphas of FLEX factors*

| | Contained | Optimistic | Prudent | Engaged |
|---|---|---|---|---|
| Overall | 0.80 | 0.88 | 0.77 | 0.66 |

*Table 8: Cronbach's Alphas of COPE factors.*

# Conclusions.

The further statistical evaluation of 'Spotlight' presented in this brief report demonstrates the competence of 'Spotlight' as a personality evaluation tool, expanding the exploratory approach of previous work (Ong, 2018). This is evidenced by the robust factor structures of FLEX and COPE and good reliability of the items in each of the factors.

### References.


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