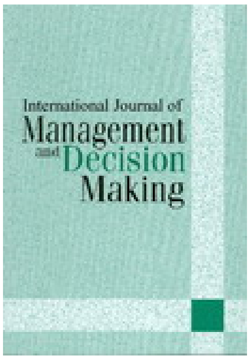

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Predictive analytics for efficient decision making in personnel selection

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Abstract: This study investigates the predictive modelling in personnel selection. In particular, we focus on the prediction of interview performance using combinations of variables which assess personality and cognitive ability. Based on a dataset of 1,989 subjects, we generate 1,024 possible models with ten predictors including six personalities and four cognitive factors and apply the mixed-effect logistic regression to account for the random effect. The predictive performance of each model is evaluated by the area under receiver operating characteristic curve. The results show that the model with a combination of ambition and agreeableness as well as verbal and reasoning can predict the interview performance at 68% accuracy and this predictive power is not substantially different from the predictive performance of more complicated models. Our results suggest that personnel selection with fewer factors can be as efficient as all factors in the prediction. This study contributes to the selection literature by emphasising and justifying efficient decision making with predictive models, and it demonstrates that the personnel selection procedure can be simplified in an organisation and can save the organisation resources.

Keywords: predictive modelling; personnel selection; personality; cognitive ability; interview performance.

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1 Introduction

Personnel selection is not only one of the influential topics in academia, but also has sustainable impact on individuals, team, and organisations (Lievens et al., 2021). Organisations spend long time on hiring people since it is very difficult to correct the consequences from the wrong decision about hiring one person (Liao and Chang, 2009). Too much time and cost will be spent on engaging, training, and firing of poor or disappointing employees and the costs increase if it takes a long time to realise that an employee is inadequate (Afshari et al., 2014). Human ability and personality consist of many factors, and assessments on all factors are practically infeasible. Some factors are even highly correlated. For these reasons, personnel selection should be an effective and efficient decision-making process. Personnel selection studies have emphasised that usages of rigorous selection tests can benefit to identify valuable talents for contributing to job performance. Employment tests were first introduced in the 1920s (Ghiselli, 1966), and a variety of selection methods including work sample tests, assessment centres, employment interviews, job knowledge tests, bio-data measures, and personality and cognitive ability tests have been studied to show their predictive validities (Ghiselli, 1973; Hunter and Hunter, 1984; Reilly and Chao, 1982; Le et al., 2007; Anglim et al., 2021). For the effective decision-making in personnel selection, researchers have been interested in the development of key predictors (Arthur and Villado, 2008).

Specifically, a number of studies in personnel selection have shown that cognitive ability and personality tests and interview performance are related. Hunter and Hirsh (1987) and Schmidt (1988) have argued that the validity of the interview performance correlated with cognitive ability. Fletcher (1987) and Cook et al. (2000) have suggested a relation between personality and interview outcomes exists. Cortina et al. (2000) suggested that interview scores explain the job performance better than cognitive ability and conscientiousness. If the interview performance better explains the future job performance, time and resources can be saved by predicting the interview performance and making data-driven intermediate decisions during the personnel selection process. The past studies have focused on the theoretical perspective via statistical significance in hypothesis testing, but there has been a lack of attention on the predictability. In addition, since predictive analytics in human resource management (HRM) have received much attention from the scholars, we can utilise new analysis methods like machine learning (Singh et al., 2022). From the practical perspective, particularly for employers, it is important to examine and quantify the predictability of the cognitive and personality tests on the interview performance. Even so, there is a lack of previous studies to investigate the predictability using predictive analytics. To contribute to the literatures, this study focuses on the predictive modelling for interview performance through the combination of personality and cognitive ability.

The main objective of this study is to find the most efficient combination of personality and cognitive ability factors to predict the interview performance. For the selection decision-making, studies tend to pay attention to the development of predictors and its effectiveness (Arthur and Villado, 2008). However, along with the effectiveness, efficiency also matters in the practical decision-making process of personnel selection. Selection with fewer factors can be as efficient as all factors in the prediction. Efficient decision-making in personnel selection can be linked with the decisions using less organisational resources. In particular, under the uncertain situation with COVID-19 and digital transformation, organisations need to run efficiently (Caligiuri et al., 2020).

Our contribution is to extend the academic findings to practical settings by suggesting an effective and efficient decision-making case in personnel selection. Another contribution is to turn readers' attention from statistical significance to practical significance in personnel section and HRM in general. In large datasets, even weak relationships among scaled variables can lead to statistically significant results (i.e., small p-values), but the actual predictive performance of these variables matters in practice (i.e., how often the prediction is correct). Furthermore, this study explains the difference between predictive analytics and hypothesis testing that scholars and practitioners are sometimes confused with the distinctive concepts and the applications. Most academic findings are about associations between variables via hypothesis testing. However, practitioners, who actually need to make decisions and take actions, want to know the practical significance of these findings. In other words, results from hypothesis testing help better understand the population-level relationships, whereas predictive models help practitioners make individual-level decisions and take specific actions. To this end, this study is motivated by the practicality, and we emphasise the importance of predictive analysis for the efficient and effective decision-making in personnel selection, which leads to making a practical contribution.

2 Literature review

2.1 Decisions in personnel selection

Personnel selection has emphasised predictive efficiency (Lievens and Highhouse, 2003). In recent years, more organisations are considering how to run smarter, more agile, and more efficient businesses by using the right data to support effective and efficient decision making (Davenport, 2006; Haddad et al., 2019; Zaitsava et al., 2022). Efficient decision making in human resource (HR) refers to having more outputs through less inputs. For example, an efficient hiring process would result in minimised (or reduced) cost per hire, HR staff per employee, and the time to train (Boudreau and Ramstad, 2005).

However, minimising cost and time to finish a hiring process should not be a sole criterion. The main purpose of personnel selection is to hire the applicants who are most likely to perform well when she/he joins the organisation. In that sense, decision making in personnel selection is about predicting future performance. In personnel selection research, many studies have examined the predictive validity of selection methods (e.g., Barrick and Mount, 1991; Caldwell and Burger, 1998). Organisations have used a variety of selection tools such as cognitive ability, employment interview, personality instrument, motivation test, and assessment centre to name a few. Among them, interview, cognitive ability test, and personality instrument have been utilised most frequently due to its high criteria validity. The studies have examined the criterion-related validity of cognitive ability, personality, and interview tests and the most consistent finding is that cognitive ability test is one of the strongest factors for predicting job performance (Ones et al., 2010; Schmitt, 2014; Landers et al., 2021). Schmidt and Hunter (2000, p.4) have suggested that intelligence such as general mental ability and general cognitive ability play important roles for predicting employee job performance and can be considered as 'the most 'successful' trait in applied psychology'.

Although studies have shown that cognitive ability largely predicts employee job performance, it does not necessarily mean that cognitive ability alone is the best way to hire the applicants. The combination of cognitive ability test and personality instrument can explain 20% more variance in job performance than a cognitive ability test can explain by alone (Schmidt and Hunter, 2000). Also, structured employment interviews can add 14% incremental validity to cognitive ability tests (Oh et al., 2008). In addition to cognitive ability tests, the two predictors, such as personality instruments and employment interviews, have received considerable attention in the workplace, due to their predictive capabilities and potential to lessen the adverse impact associated with cognitive ability tests (Hunter and Hunter, 1984).

Personality tests also have a sufficient predictive power for job performance. Personality is defined as an individual's relatively stable and enduring pattern of thoughts, feelings, and actions (Barrick and Mount, 1991), and personality predicts various behavioural outcomes (Ozer and Benet-Martinez, 2006). Because of its predictability, personality tests have been popular and widely used in employee selection (Hough and Oswald, 2008; Günaydin, 2021). Meta-analytic studies have shown that the Big Five personality traits account for about 50% of the variability in adaptive performance at work, leadership emergence and effectiveness (Huang et al., 2014; Judge et al., 2002) and cognitive ability up to 27% (Judge et al., 2004). Barrick and Mount (1991) and Tett et al. (1991) provided the evidence that the Big Five personality might be useful to select employees in various jobs. The instruments show positive relationships with performance criteria for various jobs (Barrick and Mount, 1991; Hurtz and Donovan, 2000).

For the research of personnel selection, incremental validity is important since each selection tool explain different criteria of job performance. If selection tool evaluates the same point and is strongly associated with each other, there is no reason for the tools to be more than two. In that sense, incremental validity can be significant concept in personnel selection research (Burgoyne et al., 2021). For instance, incremental validity of personality instrument in predicting performance over and above more traditional selection methods such as cognitive ability test (Day and Silverman, 1989; McHenry et al., 1990). The personnel selection research shows that using job-relevant personality tests leads to a meaningful incremental validity over cognitive ability (Oh et al., 2011). Therefore, it is better to use both of cognitive ability and personality instruments to improve their incremental validity.

The employment interview continues to be one of the most popular selection tests to identify valuable talents (Posthuma et al., 2002). The interview tends to be a final part of the process, and it requires relatively expensive resources when compared to earlier parts of the process. General and HR managers tend to believe that the interview is valid for predicting future job performance (McDaniel et al., 1994). There have been several recent meta-analyses of the reliability and validity of the interview (Conway et al., 1995; Huffcutt and Arthur, 1994; Huffcutt et al., 1996; Wiesner and Cronshaw, 1988) suggesting that employment interviews are positively related to job performance and training success. Schmidt and Hunter (1998) have shown that the interview is one of the best predictors of job performance and that the validity of interview test works well across jobs, criteria and organisations.

This study focuses on the relationship between various selection tests (e.g., cognitive ability and personality) and interview performance. Although some studies have examined how selection tests predict interview performance (e.g., Huffcutt et al., 1996; Tay et al., 2006), little research has paid attention to this relationship based on predictive analytics. Considered the predictive validity of employment interview on performance in the future, the study has yet to receive much attention. In particular, selection tests can be conducted based on the multiple screening steps in the selection process, so the multiple screening systems can reduce a large pool of job applicants to a smaller sample following the causal selection steps (Gatewood et al., 2008).

Generally, cognitive-and non-cognitive-based selection tests such as cognitive ability and personality tests are conducted in the initial stage, to screen out less valuable applicants and enhance the quality of applicants in the interview process. Some studies show that some selection evaluations such as conscientiousness, extraversion, or cognitive ability predict interview performance (e.g., Boudreau et al., 2001; Caldwell and Burger, 1998).

2.2 Predictive analytics

Predictive analytics can be defined as an analyst-guided subject that examines data patterns to make forward-looking predictions (Mishra and Lama, 2016). There are different kinds of analysis including descriptive analysis, predictive analysis, and prescriptive analysis (Bertsimas and Kallus, 2020; Sheng et al., 2021). Unlike confirmatory analysis, which typically draw conclusions based on p-values, predictive analytics focuses on guessing the value of an outcome to be observed in future (Margherita, 2021). The distinctions should be made based on the primary purpose of analysis, and appropriate statistical strategies should be chosen according to the purpose. Predictive analytics is unlike descriptive analysis which considers external benchmarking data and involves tables, reports, ratios, metrics, dashboards or complex math; it is about data-driven insights for better decisions (Mishra and Lama, 2016). Predictive analysis can be applied to increase the probability of selecting the most appropriate candidate for a job (King, 2016). Some management issues can be efficiently addressed by predictive analytics (Mishra et al., 2016). Because of its diverse utilities, predictive analysis has received close attentions by HR professionals and scholars (Lee et al., 2020).

Data mining, decision trees, pattern recognition, forecasting, and root-cause-analysis are frequently applied for predictive modelling (Watson, 2011). Classification and regression tree algorithm are popular techniques in personnel selection decision-making (Azar et al., 2013). The *K*-means and decision tree algorithms have been applied for decision making on recruiting employees (Sivaram and Ramar, 2010). The predictive performance should be validated outside of a sample, and cross-validations is a population method for this purpose (Kutner et al., 2004). Unlike hypothesis testing where a model is to be prespecified, predictive modelling is relatively liberal in a sense that multiple models can be compared and a best model can be chosen based on the predictive performance. Furthermore, the interpretations of model parameters are relatively less important in prediction than in hypothesis testing.

Although there are differences between hypothesis testing and prediction, researchers and professionals are frequently confused with their concepts and utilities (Shmueli, 2010). Prediction is an effort to see future happening advance and focus on which variables are to be combined and in which functional form in order to maximise the accuracy of prediction. On the other hand, hypothesis testing is to prove the relationship between variables (Shmueli and Koppius, 2011), so variables are to be chosen based on researchers' hypotheses. In that sense, a model for the purpose of hypothesis testing and a model for the purpose of best prediction do not have to the same, and they may be substantially difference because the real world is often more complicated than the hypothetical setting.

The purpose of personnel selection is to hire high-potential candidates who are likely to perform in the future. Therefore, using the personality instrument and cognitive ability test which are theoretically important, this study focuses on solving the theoretical issue and practical problem by finding an optimal combination of the potential predictors to maximise the accuracy of forecasting the interview performance, which is closely related to future job performance.

3 Method

3.1 Data

This study was conducted with a sample of employees in a South Korean conglomerate. The company has retail, food, service, hotel, chemical, and other industries and has expanded to 31 countries with more than 100,000 employees at home and abroad. The recruitment system of South Korean corporates tends to rely on open recruitment and testing (Koch et al., 1995). Open recruitment system is an attempt to attract university graduates and hire the employees on a bi-annual basis (Lansbury et al., 2006). The focal company tends to hire more than 2,000 employees out of 60,000 applicants on average. There are three steps for the recruitment process starting with resume screening, cognitive ability test and personality instrument, and lastly interview.

Since more than 30,000 students apply for the recruitment process on every semester, HR team spends many resources and tries to make efficient as well as effective decision-making. In order to solve the efficiency problem of open recruitment system, HR team asked the authors to suggest the efficient decision-making solution. HR team provided the sample dataset that was gathered in 2017 to 2018 without personal identifiable information.

3.2 Measurement

The personality instrument consists of six factors including Big Five personality plus ambition and the cognitive ability has four parts including verbal, math, logic and spatial reasoning. In total, there are ten factors to assess the applicant's personality and cognitive ability. The dataset was organised for the predictive analysis including neuroticism (referred to as O1; alpha = 0.885), ambition (O2; alpha = 0.806), extraversion (O3; alpha = 0.913), agreeableness (O4; alpha = 0.881), conscientiousness (O5; alpha = 0.843), openness to experience (O6; alpha = 0.827). Personality inventories are derived from Costa and McCrae (1992) and Hogan and Hogan (1995). The instrument is based on ipsative scale and sample items are 'I am emotionally stable, not easily upset' for neuroticism, 'I try to be better than everyone else' for ambition, 'I am full of energy' for extraversion, 'I am helpful and unselfish with others' for agreeableness, 'I do a thorough job' for conscientiousness, and 'I am curious about many different things' for openness to experience.

Moreover, in the cognitive ability test, four types of items were used including verbal analogies (referred to as A1; 30 verbal items), number series (A2; 25 number series), symbolic analogies (A3; 25 spatial items), and inductive and deductive (A4; 30 reasoning items). For the structured employment interview, two interviewers participated in the process and raise competency-related questions for more than an hour. On average, three competencies were assessed in an interview and they varied in the jobs that applicants applied. For example, those who applied sales manager in the mart were expected to have achievement-related questions such as 'please tell us your experience that you have achieved more than you expected'. Then, probing questions (i.e., checking the information about the answers in detail) follows after the applicant's responses.

3.3 Statistical analysis (predictive models)

There were 47 companies observed in the data, and a mixed-effect logistic regression was considered to account for the random effect. The outcome variable to be predicted was whether a subject passed the interview or not. There were ten predictors including O1, O2, O3, O4, O5, and O6 and A1, A2, A3, and A4, so there were $2^{10} = 1{,}024$ possible models (considering the first-order additive terms only). Since there were a large number of models, top predictive models were potentially selected based on information criteria. The Akaike information criterion (AIC) (Akaike, 1974) and the Bayesian information criterion (BIC; Schwarz) are two well-known methods for model selection, but AIC and BIC often suggest different models (Dziak et al., 2020). Both the AIC and the BIC can be derived from a model's likelihood function based on the maximum likelihood estimates (Vrieze, 2012).

There is no single best method for model selection, arguing that both criteria should be considered (Kuha, 2004). The AIC tends to tolerate over-parameterisation, and BIC tends to prefer parsimonious model particularly in a large sample size. Since their properties are different, we selected top five models under each criterion out of the 1,024 candidate models, and we compared their predictive performances using five-fold cross-validations (Kutner et al., 2004). For the binary prediction (i.e., passing the interview or not), the predictive performance depends on the classification threshold (i.e., the estimated probability of passing). To measure the overall predictive performance of each model across all threshold values (from zero to one), the area under receiver operating characteristic (ROC) curve was estimated. The background and detail explanations of the ROC curve are provided in Bradley (1997) and Hajian-Tilaki (2013). The area under ROC curve is a value between zero and one, such that a higher value indicates a better overall predictive performance.

4 Results

4.1 Descriptive statistics, AIC and BIC

The sample means, standard deviations (SDs), and correlations of the 10 predictors are summarised in Table 1. The predictors O1 to O6 were moderately correlated and A1 to A4 were also moderately correlated, but the correlations between O's and A's were relatively weak. When models were selected based on AIC or BIC, the predictor O1 seemed not important, and BIC resulted in more parsimonious models with three to five predictors (Table 2). According to the BIC, A2 and A3 were not included together, and it seemed only A1 and A4 were sufficient in a model.

4.2 Sensitivity, specificity, and area under ROC curve

In Table 2, the sensitivity (correctly predicting passing subjects), specificity (correctly predicting non-passing subjects), and the area under ROC curve (AUR) are presented after the cross-validations. The best model chosen by BIC (M1-B) resulted in sensitivity, specificity, and AUR of 0.629, 0.608, and 0.663, respectively. The best model chosen by AIC (M1-A) resulted in 0.633, 0.610, and 0.666, respectively. These results are similar to the results of the full model (i.e., using all ten predictors) which are 0.629, 0.613, and

0.664, respectively. The predictive performance was not lost by removing the two variables O1 and O3 (M1-A), and the loss of predictive performance was nearly negligible (less than 0.005; 0.5%) by removing the four more variables O5, O6, A2, and A3 (M1-B).

Table 1 Descriptive statistics (means, standard deviations, and correlations) of the ten predictors

Predictor	*Mean*	*SD*	*O1*	*O2*	*O3*	*O4*
O1	55.9	30.3	-	0.321	0.602	0.482
O2	49.4	30.0	0.321	-	0.504	0.317
O3	56.5	33.0	0.602	0.504	-	0.522
O4	62.7	32.1	0.482	0.317	0.522	-
O5	64.5	31.2	0.388	0.219	0.323	0.376
O6	49.9	31.6	0.328	0.418	0.512	0.371
A1	49.6	11.7	–0.011	–0.019	–0.028	0.000
A2	55.0	10.1	–0.005	–0.06	–0.009	–0.031
A3	52.6	10.6	0.049	–0.016	–0.002	0.009
A4	46.9	13.3	0.061	–0.025	0.014	0.034
Predictor	*O5*	*O6*	*A1*	*A2*	*A3*	*A4*
O1	0.388	0.328	–0.011	–0.005	0.049	0.061
O2	0.219	0.418	–0.019	–0.060	–0.016	–0.025
O3	0.323	0.512	–0.028	–0.009	–0.002	0.014
O4	0.376	0.371	0.000	–0.031	0.009	0.034
O5	-	0.174	0.005	0.023	0.010	0.024
O6	0.174	-	–0.029	–0.066	–0.080	–0.032
A1	0.005	–0.029	-	0.345	0.413	0.426
A2	0.023	–0.066	0.345	-	0.383	0.377
A3	0.01	–0.080	0.413	0.383	-	0.475
A4	0.024	–0.032	0.426	0.377	0.475	-

Note: O1 = neuroticism; O2 = ambition; O3 = extraversion; O4 = agreeableness; O5 = conscientiousness; O6 = openness to experience; A1 = verbal; A2 = numerical; A3 = spatial; A4 = reasoning.

Figure 1 The distributions of estimated probabilities of passing interview (full model, best model selected by AIC and best model selected by BIC) between subjects who passed the interview and subjects who did not pass the interview

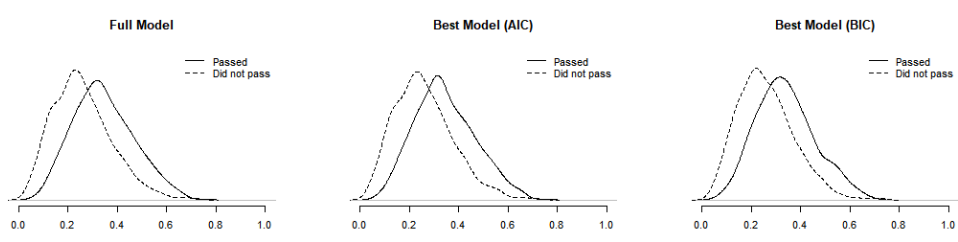

Figure 1 supports the use of the simple model M1-B instead of M1-A or the full model. The figure distinguishes the estimated probabilities of passing the interview between those who actually passed and those who did not pass. The distributions of estimated probabilities are nearly identical among the three models, so the four predictors in M1-B may be as good as the eight predictors in M1-A or all 10 predictors.

Table 2 Five models selected by AIC (M1-A to M5-A) and five models selected by BIC (M1-B to M5-B), and their predictive performance measured by sensitivity, specificity, and area under ROC (AUR)

Model name	*Model*	*AIC*	*BIC*	*Sensitivity*	*Specificity*	*AUR*
M1-A	O2 + O4+ O5+ O6 + A1 + A2 + A3 + A4	2,247.29	2,297.65	0.633	0.610	0.666
M2-A	O2 + O3+ O4 + A1 + A2 + A3 + A4	2,247.39	2,292.15	0.632	0.612	0.667
M3-A	O2 + O3 + O4 + A1 + A2 + A4	2,,247.52	2,286.69	0.631	0.608	0.667
M4-A	O2 +O3+ O4 + O5 + A1 + A2 + A3 + A4	2,247.63	2,297.99	0.635	0.615	0.666
M5-A	O2 + O4 + O6 + A1 + A2 + A3+ A4	2,247.70	2,292.46	0.631	0.609	0.666
M1-B	O2 + O4 + A1 + A4	2,252.14	2,280.12	0.629	0.608	0.663
M2-B	O2 + O4 + A1 + A2 + A4	2,248.34	2,281.91	0.627	0.606	0.665
M3-B	O3 + O4 + A1 + A4	2,255.28	2,283.26	0.628	0.608	0.663
M4-B	O2 + O4 + A1 + A3 + A4	2,250.57	2,284.14	0.630	0.611	0.664
M5-B	O2 + O3 + O4 + A1 + A4	2,251.01	2,284.58	0.634	0.610	0.664

Note: O1 = neuroticism; O2 = ambition; O3 = extraversion; O4 = agreeableness; O5 = conscientiousness; O6 = openness to experience; A1 = verbal; A2 = numerical; A3 = spatial; A4 = reasoning.

Table 3 Estimated parameters of M1-B and of M1-B with the interaction terms

	M1-B				*M1-B with the interaction terms*				
	Estimate	*SE*	*Z*	*P-value*		*Estimate*	*SE*	*Z*	*P-value*
Intercept	–1.154	0.100	–11.581	< 0.001	Intercept	–1.024	0.102	–10.007	< 0.001
O2	0.193	0.056	3.450	< 0.001	O2	0.224	0.056	3.972	< 0.001
O4	0.228	0.056	4.069	< 0.001	O4	0.210	0.056	3.734	< 0.001
A1	0.309	0.062	4.985	< 0.001	A1	0.330	0.065	5.051	< 0.001
A4	0.258	0.061	4.225	< 0.001	A4	0.275	0.064	4.273	< 0.001
					O2 × O4	–0.200	0.055	–3.644	< 0.001
					A1 × A4	–0.312	0.069	–4.521	< 0.001

Note: O1 = neuroticism; O2 = ambition; O3 = extraversion; O4 = agreeableness; O5 = conscientiousness; O6 = openness to experience; A1 = verbal; A2 = numerical; A3 = spatial; A4 = reasoning.

The four predictors of M1-B (see Table 3) could be utilised better by including the multiplicative terms between O2 and O4 and A1 and A4 (i.e., interaction terms). This multiplicative model resulted in sensitivity of 0.679, specificity of 0.559, and AUR of 0.676. There was a trade-off between sensitivity and specificity. In this dataset, 564 subjects passed the interview and 1,425 subjects did not pass. By utilising the four predictors (O2, O4, A1, and A4) multiplicatively, the sensitivity increased from the baseline 0.284 to 0.679, and the specificity decreased from the baseline 0.716 to 0.559 as a trade-off.

5 Discussion

5.1 Summary and general discussion

In this study, we aim to find out the right combination of personality and cognitive-ability factors for efficient decision-making in personnel selection, using predictive analytics. The accuracy of prediction through this combination is as almost same as the all predictors. The growing attention upon efficient recruitment process requires more effort to understand efficient decision making in personnel selection. This reason led to us using predictive analytics to explain its effectiveness (Mishra et al., 2016).

Organisations have the growing needs for efficiently and cost-effectively recruiting and selecting valuable talents in the labour market. Since the pandemic of COVID-19, the number of jobs has decreased across the globe (International Labour Organisation, 2020) and unemployment rate has been on rise (Kawohi and Nordt, 2020). As more applicants compete for a limited number of positions, screening process in the early stage of personnel selection has become more important. Even long before the pandemic, Skinkle and McLeod (1995) have discussed the importance of predictive validity of selection methods (i.e., personality instrument, cognitive ability test) before the interview due to the limitation of interview. Since data collection has been more accurate and efficient due to technological advance and since each organisation has its own subpopulation (Devi et al., 2020), the organisations are encouraged to develop its own predictive models to accurately and efficiently predict applicant's performance (Hastuti and Timming, 2022).

5.2 Implications

This study focuses on predictive analysis of personality instrument and cognitive ability to predict interview performance. Our findings show that combining a smaller number of personality factors (ambition and agreeableness) and cognitive ability (verbal and reasoning) is as effective as combining all ten available predictors in the personality and cognitive ability. In the organisations, HR spends tremendous amount of money and efforts to develop personality instrument and cognitive ability and takes long time and high energy to operate them. If we can reduce the number of factors by removing weak predictors in personality instrument and cognitive ability test, it can practically contribute to saving resources for personnel selection and those saved resources can be allocated to employment interview.

This study also demonstrates that not all theoretically validated variables are equally useful in practice. Although many theoretical studies gained sufficient attention by HR scholars these days, there are relatively few empirical studies in the HR field (Marler and

Boudreau, 2017; McCartney and Fu, 2022). This study contributes to personnel selection research by empirically conducting the predictive analysis for efficient HR decision-making, since predictive analytics have much attention from both scholars and practitioners.

5.3 Limitations and future research

Our study has some limitations. First, the data was collected from a single firm. We may not confidently generalise our results across firms, industries, and countries. To generalise our findings, future research needs to replicate our model, using different samples from different industries or countries. Second, this study used six factors for personality instrument and four factors in the cognitive ability test. However, a variety of personality and cognitive factors exist for the recruitment decision-making. Accordingly, future research may need to explore the different factors for predictive analytics to find another efficient combination of factors. Lastly, because advance in technologies such as artificial intelligence, machine learning, and deep learning can enhance the predictability for personnel selection, future research will be able to utilise those technologies for the research purpose.

5.4 Conclusions

The predictive analysis in the personnel selection can be simplified by including a few key predictors instead of using all available predictors without losing the predictability.

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