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SAMPLE SIZE FOR SURVEY RESEARCH: REVIEW AND RECOMMENDATIONS

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ABSTRACT

Determining an appropriate sample size is vital in drawing realistic conclusions from research findings. Although there are several widely adopted rules of thumb to calculate sample size, researchers remain unclear about which one to consider when determining sample size in their respective studies. 'How large should the sample be?' is one the most frequently asked questions in survey research. The objective of this editorial is three-fold. First, we discuss the factors that influence sample size decisions. Second, we review existing rules of thumb related to the calculation of sample size. Third, we present the guidelines to perform power analysis using the *G**Power programme. There is, however, a caveat: we urge researchers not to blindly follow these rules. Such rules or guidelines should be understood in their specific contexts and under the conditions in which they were prescribed. We hope that this editorial does not only provide researchers a fundamental understanding of sample size and its associated issues, but also facilitates their consideration of sample size determination in their own studies.

Keywords: *Sample Size, Power Analysis, Survey Research, G*Power.*

INTRODUCTION

A sampling strategy is more than often necessary since it is not always possible to collect data from every unit of the population (Kumar *et al.*, 2013; Sekaran, 2003). Hence, determining an appropriate sample size is vital to draw valid conclusions from research findings. However, it is often considered a difficult step in the design of empirical research (Dattalo, 2008). Although there are a good number of tables and rules of thumb to calculate sample size in social science research, many researchers remain unclear about which one they should use to determine the appropriate sample size in their studies, especially when their studies employ survey research for data collection. Previous literature has highlighted that sample size is one of the key limitations of empirical studies published in top journals (see Aguinis & Lawal, 2012; Green *et al.*, 2016; Uttley, 2019). Likewise, based on a meta-analysis of 74 structural equation modelling articles published in top management information system journals, Westland (2010) found that about 80 percent of all studies are based on insufficient sample sizes.

Moreover, following our work on methodological misconceptions and recommendations (Memon *et al*., 2017) as well as mediation (Memon *et al*., 2018) and moderation analyses (Memon *et al*., 2019), we received a multitude of requests from the research community, particularly from research students, for our input on sample size. We also observed that queries related to sample size were among the most frequently asked questions on social media, in emails, and in face-to-face interactions during workshops and conferences. Most questions revolved around how an appropriate sample size should be determined and/or how large a sample should be. To the disappointment of our enquirers, we often answered them with, *"There is no one-size-fits-all solution to address this issue"*. Nevertheless, we were prompted to do something about it. Instead of ignoring this perennial question or providing a textbook response, we decided to work on this topic.

The aim of this editorial is three-fold. First, we discuss some of the key factors that influence sample size, as we believe that these factors heavily impact not only initial sample size estimations but also final sample sizes. Second, we review the existing rules, tables, and guidelines that are most often used to calculate sample size. In doing so, we acknowledge and synthesise previous literature on the subject matter and explain how they should be effectively appropriated. Third, we present the guidelines to perform power analysis. Recent studies have recommended the use of power analysis for sample size calculation (Hair *et al*., 2014; Hair *et al*., 2017; Ringle *et al*., 2018). This editorial, to the best of our knowledge, is one the few studies to provide step-by-step instructions on conducting power analysis with the *G**Power programme. In addition, the editorial recommends several readings for a better understanding of issues related to sample size. We hope that our effort will not only broaden researchers' understanding of sample size and its associated concerns, but will also facilitate their consideration of appropriate sample size determination for their respective studies.

FACTORS INFLUENCING SAMPLE SIZE DECISIONS

Sample size can be defined as the subset of a population required to ensure that there is a sufficient amount of information to draw conclusions (Sekaran & Bougie, 2010). Kumar *et al.* (2013) described sample size in terms of the "total number of subjects in the sample" (p. 122). Simply, it refers to the number of respondents or observations to be included in a study. There are several factors to be considered when estimating an appropriate sample size. These factors include the research approach, analytical method, number of variables or model complexity, time and resources, completion rate, research supervisor, sample size used for similar studies, and data analysis programme.

Nature of research and statistical analysis

Research design is considered an important factor when deciding sample size. A complex model with numerous variables requires a larger dataset than a simple model with few variables. Likewise, models that incorporate moderators or multiple groups necessitate a larger sample size. The unit of analysis also influences the size of the sample. For example, research at the organisation level using top management (e.g. CEOs, CFOs, HR managers, etc.) as respondents may have a smaller sample size than research at the individual level (e.g. employees, clients, etc.). Furthermore, the type of analysis can dictate a researcher's decision on sample size. Previous literature has provided recommendations for the minimum sample size required to perform certain analyses. For example, exploratory factor analysis cannot be done if the sample has less than 50 observations (which is still subject to other factors), whereas simple regression analysis needs at least 50 samples and generally 100 samples for most research situations (Hair *et al*., 2018).

An absolute minimum of 200 samples are required for Pearson Correlation analysis (Guilford, 1954). Also, a pre-testing and/or pilot study demands a smaller sample size than a main study. Sample size guidelines for both pre-testing and pilot studies have been briefly discussed in Memon *et al.* (2017); we may revisit this matter in the near future.

Selection of data analysis programme

The selection of analytical programmes can also influence the decision on sample size. It is commonly understood that covariance-based structural equation modelling (CB-SEM) programmes (e.g. AMOS) require larger sample sizes than partial least squares structural equation modelling (PLS-SEM) programmes (e.g. SmartPLS) due to the latter's estimation techniques (Hair *et al.*, 2017; Ringle *et al.*, 2018; Ryan, 2020). Many believe that PLS-SEM is a simplified tool to run models with small sample sizes. This argument is most often falsely and misleadingly used; consequently, many studies are conducted with small sample sizes even when the target populations are large (Hair *et al.*, 2019). Later, Hair *et al.* (2017, p. 22) clarified that "no multivariate analysis technique, including PLS-SEM, has this kind of magical capabilities" (p. 22). A software programme can run any model with any sample size – this does not mean it produces accurate results. Interestingly, with large datasets (250 samples and above), both CB-SEM and PLS-SEM may yield similar results. We strongly recommend researchers to refer to Hair *et al.* (2019) for a detailed discussion on sample size in PLS-SEM research.

Research supervisor/examiner

The orientation of a research student's supervisor or examiner is another aspect that typically influences students' decision on sample size. Many supervisors and/or examiners (including those at the proposal defense) believe that a large sample size is requisite to improve generalisability of results and draw better conclusions. Therefore, they often push students or candidates to plan and collect data from as many respondents as possible. Mooi *et al.* (2018, p. 47) argued that the "gains in precision decrease as the sample size increases" (p. 47). According to Hair *et al.* (2018), large samples can make statistical significance overly sensitive, which can result in a Type 1 error. In other words, a large sample size can make any relationship statistically significant even when it is not (Hair *et al.*, 2018; Kline, 2016). This is one of the reasons researchers often coincidentally achieve highly significant results (e.g. $p < .0001$) but infinitesimal effect sizes (Sullivan & Feinn, 2012). However, we do not intend in any way to say that large samples should be abandoned. Rather, we believe that the way data is collected as part of the research design is more important than investing effort and resources into blindly collecting more data to increase sample size. The robustness of any sample depends more on the careful selection of respondents rather than its size (Boreham *et al.*, 2020; Mooi *et al.*, 2018).

Practical considerations

Budget, time, resources, and other constraints may affect sample size considerations as well (Bartlett *et al.*, 2001). It is often challenging for researchers to physically approach a geographically dispersed population due to limited financial resources. Travelling through different states to collect data or hiring enumerators to do so to secure an adequate and representative sample is both time consuming and costly. For example, though there are oil and gas plants in various Malaysian states (e.g. Malacca, Terengganu, Johor, Sabah, Sarawak), it is not logistically feasible for students to visit all these data collection points. Besides, accessibility of the subjects is another challenge that can hinder researchers' efforts for a larger sample. This is why students who propose large samples in the early phase of their research projects often cannot meet this obligation later during data collection in the field. We notice many students struggle and suffer from anxiety and stress when they fail to achieve the proposed sample size. Therefore, in situations where a large sample size is not possible, "researchers should report both the appropriate sample sizes along with the sample sizes actually used in the study, the reasons for using inadequate sample sizes, and a discussion of the effect the inadequate sample sizes may have on the results of the study" (Bartlett *et al.*, 2001, p. 49).

Mooi *et al.* (2018) proposed that researchers should consider estimating the percentage of respondents they are likely to reach, the percentage of respondents willing to participate, and the percentage of respondents likely to complete the questionnaire accurately. This can be helpful in planning sample size correctly. Moreover, we strongly recommend researchers to always provide a thorough explanation of their sampling strategy, the characteristics of the target population in relation to research problem, and the choice of tools to determine the minimum sample size, both in theses and journal papers. Practical considerations in terms of sample size are always useful to form reasoning to not only enhance methodological clarity but also to articulate the rigour of a study's design and data collection process.

EXISTING RULES/GUIDELINES OF SAMPLE SIZE

Past research suggests several ways to determine sample size. These criterions can be divided into various categories, such as item-sample ratios, population-sample tables, and general rules-of-thumb to calculate sample size.

Sample-to-item ratio

Generally recommended for exploratory factor analysis, the sample-to-item ratio is used to decide sample size based on the number of items in a study. The ratio should not be less than 5-to-1 (Gorsuch, 1983; Hatcher, 1994; Suhr, 2006). For example, a study with 30 items (questions) would require 150 respondents. A 20-to-1 ratio has also been suggested (Costello & Osborne, 2005). In this case, the same 30-item study would need 600 respondents. Studies that followed this rule include Brown and Greene (2006), Liao, So, and Lam (2015), Yeoh, Ibrahim, Oxley, Hamid, and Rashid (2016), and Forsberg and Rantala (2020), among others. Although a higher ratio is better, researchers who have difficulties meeting the above criterion due to a small sample size can refer to Barrett and Kline (1981), who argued that the sample-to-item ratio has little to do with factor stability. Interested researchers should also look at the work of Gorsuch (1983); Hatcher (1994); Suhr (2006), and Costello and Osborne (2005) for further details.

Sample-to-variable ratio

The sample-to-variable ratio suggests a minimum observation-to-variable ratio of 5:1, but ratios of 15:1 or 20:1 are preferred (Hair *et al.*, 2018). This means that though a minimum of five respondents must be considered for each independent variable in the model, 15 to 20 observations per independent variable are strongly recommended. This is in line with Tabachnick and Fidell (1989), who proposed five subjects for each independent variable as a "bare minimum requirement" for hierarchical or multiple regression analysis. Although the 5:1 ratio appears easy to follow, students should consider higher ratios (e.g. 15:1, 20:1) when determining sample size for their research works. One of the reasons we do not recommend following the 5:1 ratio is that it leads to underpowered studies. For example, a model with five independent variables would require only 25 respondents if one uses the 5:1 ratio. In practice, this is neither sufficient for most inferential analyses (Bartlett *et al.*, 2001) nor convincing to examiners/reviewers about its chance of detecting a true effect. Furthermore, the sample-to-variable rule should be used with caution if sampling or theory generalisability and data representativeness are a concern. This rule can be used for multiple regressions and similar analyses instead. We recommend reading *Multivariate Data Analysis* by Professor Joseph F. Hair and colleagues (Hair *et al.*, 2010, 2018) for more details on the sample-to-variable method.

Krejcie and Morgan's table

The Krejcie and Morgan table (KMT, Krejcie & Morgan, 1970) is well known for sample size determination among behavioural and social science researchers. No calculations are required to use this table, which is also applicable to any defined population. The KMT suggests that a sample of 384 is sufficient for a population of 1,000,000 or more. For this reason, 384 has been regarded as the 'magic' number in research and has consequently been used in hundreds and thousands of articles and theses thus far. In addition, a sample must be representative of the particular population under study when using the KMT. Unfortunately, researchers often use this method mechanically without understanding its underlying assumptions. We urge future studies not to use the KMT thoughtlessly. The KMT should be used to determine sample size when probability sampling (e.g. simple random, systematic, stratified) is the appropriate choice. We understand that probabilistic sampling techniques are often difficult to employ due to the unavailability of a sampling frame (Memon *et al.*, 2017), such as in tourism studies (Ryan, 2020). Therefore, those who intend to use non-probabilistic sampling techniques (e.g. purposive, snowball, quota) may consider other options to determine sample size (e.g. power analysis). A similar table to the KMT can be found in Sekaran and Bougie's (2016) *Research Methods for Business: A Skill Building Approach.* Sahyaja and Rao (2020), Othman and Mahmood (2020), Yildiz *et al.* (2020), Kubota and Khan (2019), Papastathopoulos *et al.* (2019), Baluku *et al.* (2016), Collis *et al.* (2004), and Kotile and Martin (2000) are just a few of the many studies in which the KMT has been used to estimate sample size. To understand problems related to probability and non-probability sampling strategies, researchers should refer to Memon *et al.* (2017), Hulland *et al.* (2017), and Calder *et al.* (1981). We also encourage interested researchers to read and understand the original paper by Krejcie and Morgan (1970) before using the KMT in their research.

Online calculators

Similar to the KMT (Krejcie & Morgan, 1970), there are various online calculators available to determine sample size. The Raosoft sample size calculator (Raosoft, 2010) and Calculator.net (Calculator.net, 2015) are among the better known ones. Given their ease of use, these calculators have been frequently applied in social science research (see Amzat *et al.*, 2017; Cruz *et al.*, 2014; Fernandes *et al.*, 2014; Mazanai & Fatoki, 2011; Nakku *et al.*, 2020; N. Othman & Nasrudin, 2016). Online calculators typically require inputs for a study's confidence level, margin of error, and population size to calculate the minimum number of samples needed. In our experience, the KMT, Raosoft, and Calculator.net are undoubtedly useful in determining sample size. However, researchers should always be mindful of their assumptions pertaining probability sampling techniques and should thus make informed decisions about the use of these tools instead of treating them as template solutions for sample size calculation.

A-priori sample size for structural equation models

The A-priori sample size for structural equation models (Soper, 2020) is a popular application among users of 2nd generation multivariate data analysis techniques (e.g., CB-SEM, PLS-SEM). It is a 'mini' online power analysis application that determines the sample size needed for a research that uses the structural equation modelling (SEM) technique. It requires inputs for the number of observed and latent variables in the model, the size of the expected effect, as well as the anticipated probability and level of statistical power. The application generates the minimum sample size essential for detecting a specified effect given the structural complexity of the model. Because of its ability to determine a study-specific minimum sample size (based on the number of latent and observed variables), it is deemed superior to other online sample size calculators. It can be considered for any research design regardless of whether the research employs a probability or non-probability sampling technique for data collection. Valaei and Jiroudi (2016), Balaji and Roy (2017), Dedeoglu *et al.* (2018), Yadav *et al.* (2019), and Kuvaas *et al.* (2020) are among the few studies that have employed A-priori sample size calculation in their structural equation models.

Roscoe's (1975) guidelines

Roscoe's (1975) set of guidelines for determining sample size has been a common choice in the last several decades. Roscoe suggested that a sample size greater than 30 and less than 500 is suitable for most behavioural studies, while a sample size larger than 500 may lead to a Type II error (Sekaran & Bougie, 2016). Roscoe also posited that for comparative analysis, if the data set needs to be broken into several subgroups (e.g. male/female, rural/urban, local/international, etc.), 30 respondents should be considered the minimum for each group. The logic behind the rule of 30 is based on the Central Limit Theorem (CLT). The CLT assumes that the distribution of sample means approaches (or tends to approach) a normal distribution as the sample size increases. Although a sample size equal to or greater than 30 is considered sufficient for the CLT to hold (Chang *et al.*, 2006), we still urge researchers to apply this assumption with care. For multivariate data analysis (e.g. regression analysis), the sample size should be 10 times greater than the number of variables (Roscoe, 1975). Sekaran and Bougie (2016) and Kumar *et al.* (2013) discussed not only the guidelines prescribed by Roscoe (1975) in detail, but also the various procedural and statistical aspects of sample size with relevant examples. Recent studies that used Roscoe's guidelines to determine sample size include Lin and Chen (2006), Suki and Suki (2017), Seman *et al.* (2019), and Sultana (2020).

Green's (1991) procedures

Green (1991) recommended several procedures to decide how many respondents are necessary for a research. He proposed $N \geq 50+8m$ (where m refers to the number of predictors in the model) to determine the sample size for the coefficient of determination (R^2). For example, if a model consists of seven independent variables, it needs 50+(8)(7), that is, 116 samples for a regression analysis. For independent predictors (β), $N \geq 104+m$ was proposed. Thus, the minimum sample size would be 105 for simple regression and more (depending on the number of independent variables) for multiple regressions. Using this equation, 111(i.e. 104+7) cases are required if a model has seven independent variables. Fidell and Tabachnick (2014, p. 164), in turn, stated that "these rules of thumb assume a medium-size relationship between the independent variables and the dependent variable, $\alpha = .05$ and $\beta = .20$" (p. 164). Those interested in both R^2 and β should calculate N both ways and choose the larger sample size. Green (1991) believes that "greater accuracy and flexibility can be gained beyond these rules of thumb by researchers conducting power analyses" (p. 164). For further explanation, Green (1991) and Fidell and Tabachnick (2014) are good references. Studies that have determined sample size using the procedures proposed by Green (1991) include Coiro (2010), Brunetto *et al.* (2012), and Fiorito *et al.* (2007).

Sample size guidelines for PLS-SEM

The 10-times rule: Barclay *et al.* (1995) proposed the 10-times rule that was later accepted in the PLS-SEM literature. The 10-times rule recommends that the minimum "sample size should be equal to the larger of (1) 10 times the largest number of formative indicators used to measure one construct or (2) 10 times the largest number of structural paths directed at a particular latent construct in the structural model" (Hair *et al.*, 2017, p. 24). Despite its wide acceptance, doubts have been raised about this rule of thumb. It was heavily criticised by later studies that suggested it is not a valid criterion for determining sample size for PLS-SEM (Hair *et al.*, 2017; Marcoulides & Chin, 2013; Ringle *et al.*, 2018). Peng and Lai (2012) claimed that "the 10-times rule of thumb for determining sample size adequacy in PLS analyses only applies when certain conditions, such as strong effect sizes and high reliability of measurement items, are met" (p. 469). Studies that have used the 10-times rule include Wasko and Faraj (2005) and Raaij and Schepers (2008), among others. We recommend interested researchers to refer to Peng and Lai (2012) and Hair *et al.* (2017) for further details.

Inverse square root and gamma-exponential methods: As alternatives to the 10-times rule, Kock and Hadaya (2018) proposed the inverse square root and gamma-exponential methods as two new approaches to determine the minimum sample size required for PLS-SEM path models. In their Monte-Carlo simulations, Kock and Hadaya found that the inverse square root method slightly overestimates the minimum required sample size, whereas the gamma-exponential method provides a more accurate estimate. If researchers do not know in advance the value of the path coefficient with the minimum absolute magnitude, the minimum sample size required would be 160 based on the inverse square root. However, if researchers use the gamma exponential method, the sample size would be 146. The inverse square root method is recommended due to its ease of use and its basis in a simple equation. In contrast to the inverse square root method, the gamma exponential method is much more complex and is based on a computer programme. Sample studies that have used the inverse square root and gamma-exponential methods include Cheah *et al.* (2019), Gursoy *et al.* (2019), and Onubi *et al.* (2020). For more details on the use and technical aspects of the inverse square root and gamma-exponential methods, we recommend researchers to read Kock and Hadaya (2018).

Power tables by Hair et al. (2017): Hair *et al.* (2017) provided power tables to determine appropriate sample sizes for various measurement and structural model characteristics. These tables show the minimum samples required to obtain minimum R^2 values of 0.10, 0.25, 0.50, and 0.75 for any of the endogenous constructs in the structural model at significance levels of 1%, 5%, and 10% with a statistical power of 80 percent, including the complexity of a PLS path model (e.g. maximum arrows pointing to a construct). For further illustration on power tables, researchers should refer to Exhibit 1.7 in Hair *et al.* (2017).

Kline's (2005, 2016) sample size guidelines for SEM

Kline (2005) offered sample size guidelines for analysing structural equation models, suggesting that a sample of 100 is considered small, a sample of 100 to 200 is medium, and a sample over 200 is considered large. Nevertheless, Kline (2016) recognised that a sample of 200 may be too small for a complex model with non-normal distributions, particularly for those using estimation methods other than maximum likelihood. Also, any sample below 100 cases may not be recommended for any type of SEM technique unless it analyses a very simple model (Kline, 2016). Moreover, model complexity should be considered when estimating sample size. A complex model with more parameters requires a larger sample than a parsimonious model (Kline, 2005). Kline argued that SEM is a large-sample technique and certain estimates (e.g. standard errors for latent construct effects) may be incorrect when the sample size is small. We recommend SEM users to read Kline (2005) and Kline (2016) to understand sample size requirements before performing SEM.

Sample size for multilevel models

Kreft (1996) recommended the 30/30 rule for multilevel models, which dictates that 30 groups with 30 individuals per group should be the minimum sample size for a multilevel study. Later, Hox (2010) modified Kreft's 30/30 rule into a more conservative 50/20 rule, such that 50 groups with 20 individuals per group should be the minimum sample size for cross-level interactions. However, Hox believes that if researchers are interested in random elements (variance, covariance, and their standard errors), they should go with a 100/10 rule, i.e. 100 groups with a minimum of 10 individuals per group. In the meantime, scholars have recommended the use of power analysis for sample size estimation in multilevel research (see Hox & McNeish, 2020; Scherbaum & Ferreter, 2008). Statistical power can be maximised by calculating the appropriate sample sizes for each level. Power analysis can be performed through MLPowSim, a free computer programme designed to perform power estimation for multilevel models. The MLPowSim is available at https://seis.bristol.ac.uk/~frwjb/esrc.html. Hox and McNeish (2020) is a good reference for researchers interested in multilevel research.

Other rules of thumb

Aside from the rules of thumb discussed above, there are several other guidelines for determining sample size. For example, Harris (1975) recommended a minimum sample size of $N \geq 50+m$ (where m is the number of predictors). Cochran (1977) suggested that when determining sample size, researchers should identify the margin of error for the items considered most important in the survey and estimate sample size separately for each of these important items. As a result, researchers would get a range of sample sizes, i.e. small sample sizes for scaled/continuous variables and larger sample sizes for categorical/dichotomous variables. Interested researchers can refer to Bartlett *et al.* (2001) and Cochran (1977) to learn more about Cochran's sample size estimation.

Nunnally (1978) later proposed guidelines for researchers aiming to cross-validate the results of a regression analysis. In particular, Nunnally suggested that if one wants to select the best variables from as many as 10 possible ones, there should be between 400 and 500 respondents. Another rule to be referred to was put forth by Maxwell (2000), who provided a table with minimum ratios for sample sizes ranging from 70:1 to 119:1. In a similar fashion, Bartlett *et al.* (2001) developed a table that estimates sample sizes for both categorical and continuous datasets. Besides, Jackson (2003) recommended that SEM users calculate sample size using the $N{:}q$ ratio (where N is the ratio of cases and q is the number of model parameters that require a statistical estimate).

POWER ANALYSIS

Recent developments suggest that researchers should determine sample size through power analysis (Hair *et al.*, 2018; Hair *et al.*, 2017; Hair *et al.*, 2019; Kline, 2016; Ringle *et al.*, 2018; Uttley, 2019). Power analysis determines the minimum sample size by taking into account the part of a model with the largest number of predictors (Hair *et al.*, 2014; Roldán & Sánchez-Franco, 2012). It requires information related to power, effect size, and significance level to calculate the minimum required sample size (Hair *et al.*, 2018). Power (1-β error probability) is a "statistic's ability to correctly reject the null hypothesis when it is false" (Burns & Burns, 2008, p. 244). A value of 80 percent or more represents an adequate level of power in social science research (Cohen, 1988; Hair *et al.*, 2017; Uttley, 2019).

Effect size measures the magnitude of the effect that individual independent variables actually have on the dependent variable (Murphy & Myors, 2004; Sullivan & Feinn, 2012). To estimate sample size, it is necessary to know the extent of the effect in order to achieve statistical power of 80 percent or greater. Effect sizes reported in earlier studies on similar topics can be useful to set a benchmark. As a general guideline, Cohen (1988) suggested that the values of 0.02, 0.15, and 0.35 be interpreted as small, medium, and large effects respectively. The level of significance (α) relates to the probability of rejecting the null hypothesis. In social and behavioural science research, significance is generally accepted at 0.05 (5%) (Hair *et al.*, 2010).

There are various statistical programmes available to perform power analysis, such as *G**Power, SAS POWER, IBM SPSS Sample Power, Solo Power Analysis, Power, and Analysis and Sample Size System (PASS). Several free applications are available on the Internet as well. While all these programmes can be used to estimate sample size, *G**Power (Faul *et al.*, 2009; Faul *et al.*, 2007) is often the first choice for business and social science researchers (Hair *et al.*, 2014; Hair *et al.*, 2017). The detailed process of conducting power analysis using *G**Power is illustrated below.

*Power analysis using G*Power*

Figure 1 shows a simple model adopted from Memon *et al.* (2016) that examines the effects of personality traits (i.e. agreeableness, conscientiousness, and openness to experience) on knowledge sharing in the student–supervisor relationship. Figure 2 shows an extended version of the model, positioning knowledge sharing as a mediator between personality traits and student satisfaction. Figure 3 shows a moderation model that integrates supervisor feedback as a moderator between personality traits and knowledge sharing. We will refer to Figures 1, 2 and 3 for this tutorial, where *G**Power 3.1.9.7, a free software, is used to perform a power analysis.

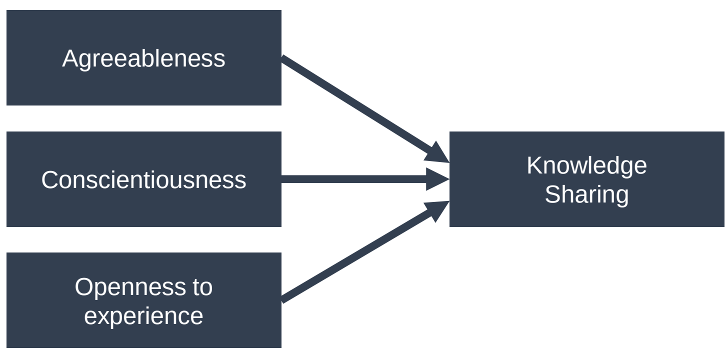

Figure 1: Simple model
Source: Memon et al. (2016)

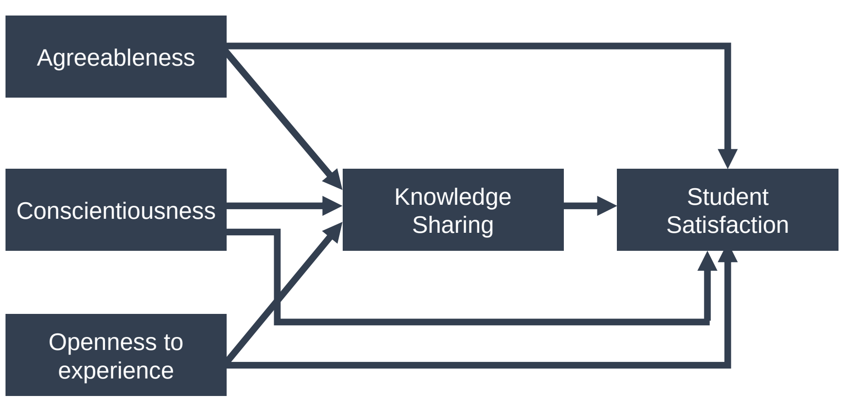

Figure 2: Mediation model

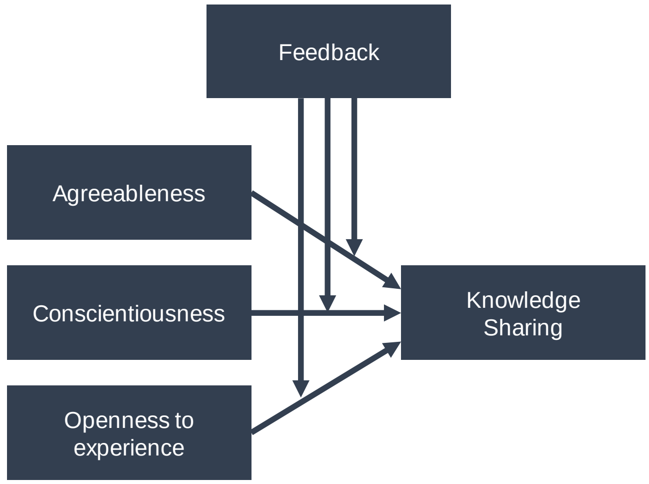

Figure 3: Moderation model (Conceptual)

To clarify, *A-priori* estimation is used for sample size estimation before data collection while *post-hoc* analysis is related to power estimation post-data collection. In this tutorial, we focus on A-priori sample size estimation. According to Uttley (2019, p. 158) "It is good practice to carry out an a priori power analysis to determine the sample size required to be confident in revealing an effect if there is one truly present". Likewise, we believe that researchers need to know the minimum sample size early on to make informed decisions and avoid post-data collection problems.

*Steps to conduct power analysis using G*Power*

Researchers must first download, install, and launch the *G**Power 3.1.9.7 programme. When the programme is open, the first step is to choose the "*F tests*" analysis from the test family options (**Step 1**). Then, select "*Linear multiple regression: fixed model, R^2 deviation from zero*" from the list of statistical tests (**Step 2**). The type of power analysis must be set at "*A-priori: Compute required sample size – given α, power and effect size*" (**Step 3**).

Next, specify the effect size at 0.15 (medium effect), α at 0.05, and power at 0.80 in the input parameters (**Step 4**). This is the most common recommended setting for social and business science research (Hair *et al.*, 2017). However, researchers are free to specify the settings that best suit their research objectives. A brief explanation of these parameters can be referred to in our earlier discussion. Following this, enter the number of predictors, which simply depends on the hypothesised model of one's study. The number of predictors refers to the maximum arrows that point to a dependent variable in the model. For the simple model (Figure 1), we have three predictors, so we enter "3" in the input parameter (**Step 5**). Then, click on Calculate (**Step 6**). *G**Power estimates that the minimum sample size required for the simple model is 77, as shown in Figure 4. These are the mandatory steps researchers should follow when they estimate power for any structural model, whether it is a simple (direct effects), moderation, or mediation model.

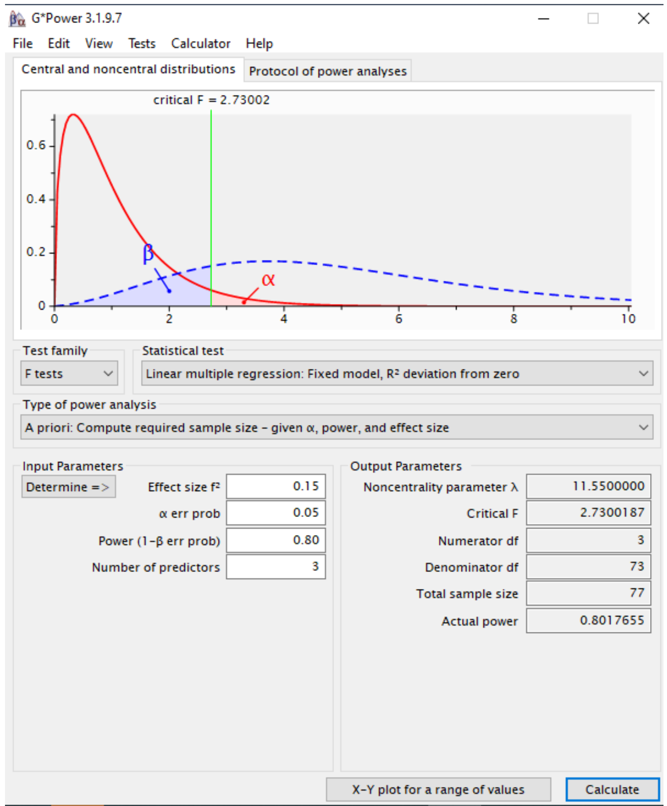

Figure 4: Power analysis for a simple model

For a mediation model (Figure 2), the steps (1-6) and input information (effect size = 0.15, α = 0.05, power = 0.80) remain constant with the exception of the number of predictors. We can observe that there are three arrows pointing to "knowledge sharing" and four to "student satisfaction". Following the rule of the maximum arrows pointing to one variable in the model, we enter "4" as the number of predictors in the input parameters. *G**Power shows that the minimum sample size required for the mediation model is 85, as shown in Figure 5.

For a moderation model (Figure 3), the steps (1-6) and information (effect size = 0.15, α = 0.05, power = 0.80) again remain constant while the number of predictors changes. Unlike simple and mediation models, the power for a moderating model is estimated based on its statistical model, which not only adds the moderator as an independent variable but also specifies the interaction terms (independent variable*moderator) of all hypothesised moderating relationships. The moderation model (Figure 3) is converted into a statistical model in Figure 6 for better reader understanding. Now, we see that seven arrows point to "knowledge sharing". Therefore, we enter "7" as the input for the number of predictors. *G**Power shows that the minimum sample size required for the moderation model is 103, as shown in Figure 7. A video tutorial with a step-by-step demonstration of how to perform power analysis using the *G**Power programme is provided for researchers to learn at their own pace and comfort (click here for the video tutorial).

To clarify, for models with formative measurements, researchers need to consider the number of indicators that form a formative construct. If the number of arrows for indicators that form a formative construct is greater than the number of arrows pointing to other constructs in the model, the number of arrows from formative indicators should be used for power analysis.

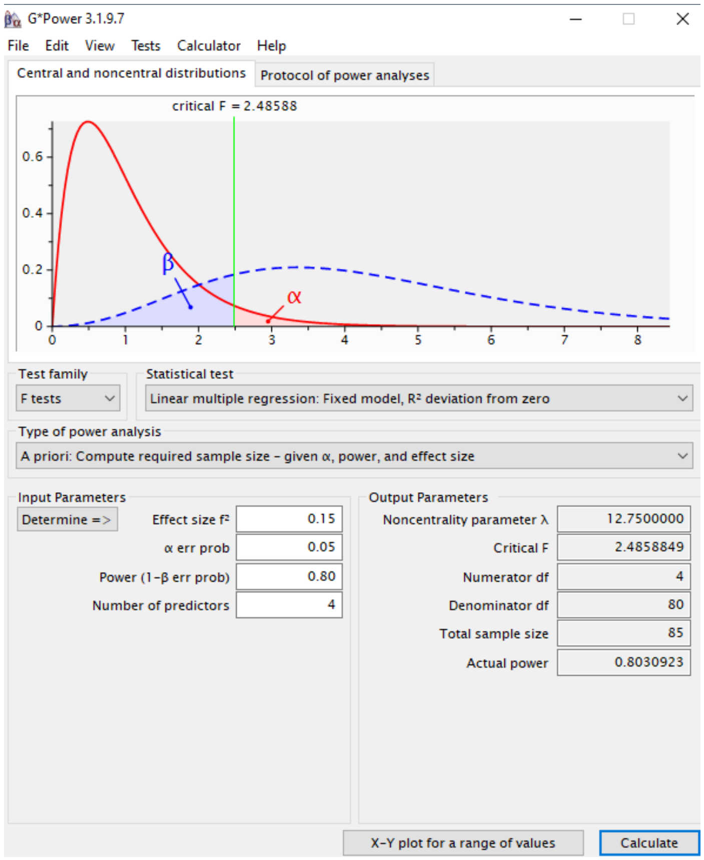

Figure 5: Power analysis for a mediation model

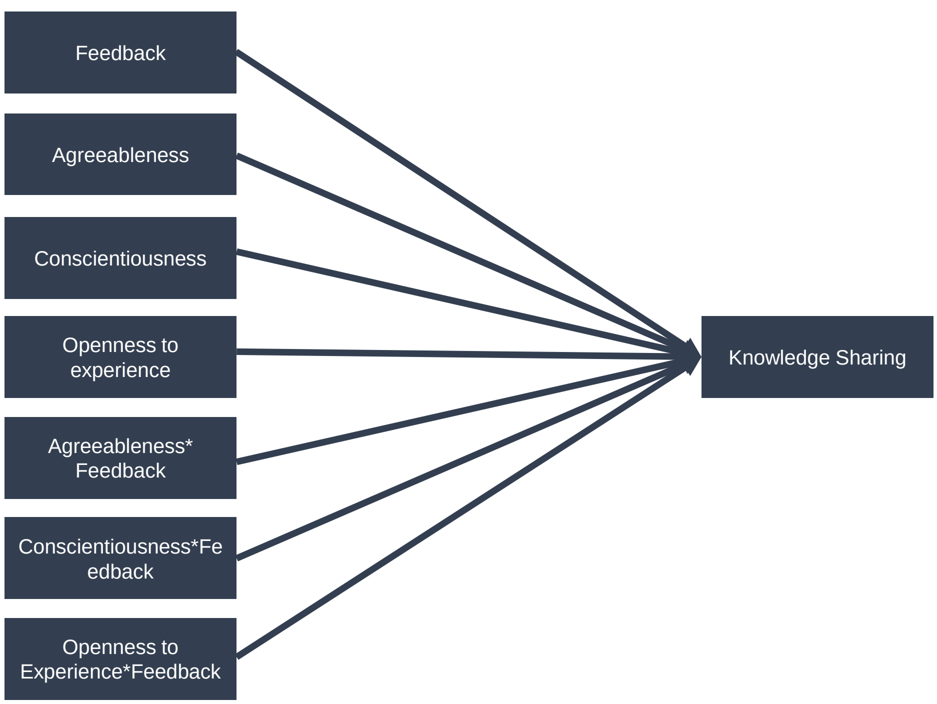

Figure 6: Moderation model (statistical)

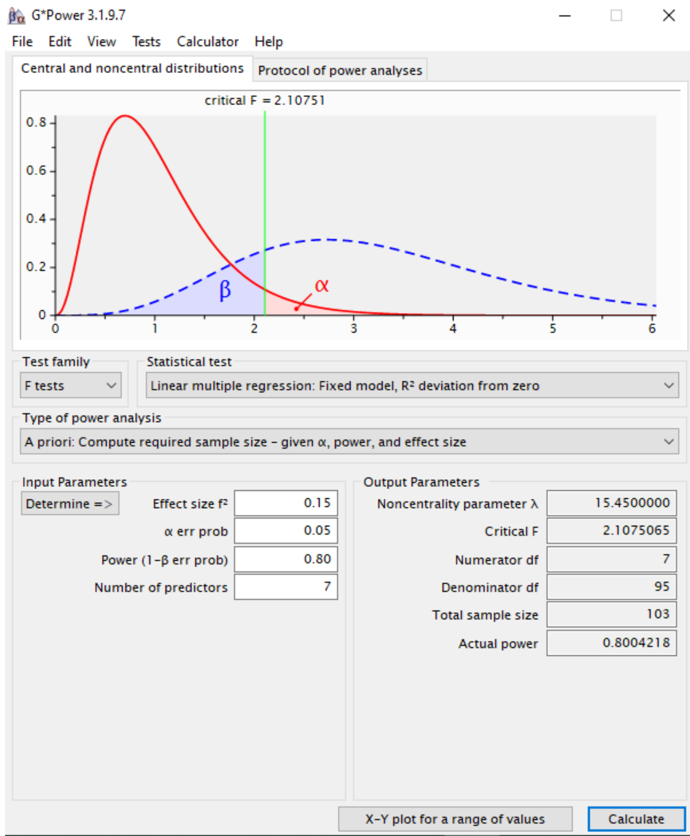

Figure 7: Power analysis for a moderation model

Recent papers by Memon *et al.* (2020), Giebelhausen *et al.* (2020), Cheah *et al.* (2019), and Awang *et al.* (2019) are just a few of the many papers that have used *G**Power for sample size estimation. For a better understanding of *G**Power, one should refer to Faul *et al.* (2009) and Faul *et al.* (2007). Also, those interested to know more about *G**Power and power estimation for other types of statistical analysis (e.g. ANOVA, ANCOVA, logistic regression, etc.) may refer to the *G**Power manual available at the official web portal (Click Here).

A FINAL NOTE

While our discussion of sample size in this editorial is by no means exhaustive, it provides, in one piece, a general view of the most commonly used guidelines and widely adopted rules for determining sample size. These rules of thumb and guidelines are mere suggestions about how large or small a sample should be based on previous empirical evidence. We urge researchers not to blindly follow these recommendations. Rather, researchers should view these guidelines and rules in their specific contexts and under the conditions (e.g. the nature of research problem, research questions, research design and the population characteristics) in which they were prescribed. Although this editorial recommends the use of power analysis to estimate sample size, it does not mean it is the only or the best option. Researchers should read and understand the rationale behind effect size, significance, and power to make informed decisions on the appropriate sample size for their research projects. To conclude, we outline the following pointers for the researcher's consideration:

1. Researchers should always apply any of these guidelines or rules with reference to the context of the study and under the conditions (e.g. the nature of research problem, research questions, research design and the population characteristics) in which they are prescribed. However, selection is important. The "strength of samples comes from selecting samples accurately, rather their sizes" (Mooi *et al.*, 2018, p. 47). Therefore, a carefully selected small sample (150 and above) is more meaningful than a blindly selected large sample (300 and above).
2. Some rules of thumb best suit certain sampling procedures. There is no harm in using these rules if researchers can fulfill their "representativeness" assumptions. For example, if the sampling frame is easily accessible for randomly selecting their respondents, researchers may consider using KMT (Krejcie & Morgan, 1970) and online calculators (e.g., RaoSoft, Calculator.net). However, most studies in social sciences and behavioural research rarely use probability sampling and thus random samples (Memon *et al.*, 2017; Polit & Beck, 2010). One of the reasons is the unavailability of the sampling frame. This is a common and practical problem faced by business and management researchers as companies are often reluctant to provide details or updated information about their stakeholders. It must be pointed out that sampling selection has nothing to do with research contribution; rather it is about appropriateness in design. In either case, justification is needed. Researchers should be aware that theory generalisability is often more important than sampling generalisability in basic research (Calder *et al.*, 1981; Hulland *et al.*, 2017; Lucas, 2003), including most MPhil and PhD studies in social sciences. It would be unwise to impose probability sampling techniques and thus generalisable sample on every research.
3. Past studies encouraged researchers to use power analysis as it determines sample size specific to model setups. Although this editorial also recommends the use of power analysis to estimate sample size, it does not mean it is the only or the best option. Researchers should read and understand the rationale behind effect size, significance, and power to make informed decisions on the appropriate sample size for their research projects. In addition, a review of previous studies, especially meta-analytical studies on the subject, can be very useful in identifying most frequently used threshold values related to power, significance, and effect size.
4. There are several absolute numbers that have been given as a rule of thumb for sample size for several decades. However, there is no single absolute number that can be used with complete confidence. A humble suggestion based on our experience is that a sample between 160 and 300 valid observations is well suited for multivariate statistical analysis techniques (e.g., CB-SEM, PLS-SEM) most of the time. It is not a small sample size nor is it considered large, so it is less likely to affect the conclusions of the study (e.g. Type I and Type II errors). That said, we do not encourage researchers to justify their sample size simply by relying on statistical programmes (e.g., AMOS, SmartPLS, WarpPLS) they use. This may be one of the justifications, but not the only justification. On another note, sample size should be matched against the target population. For example, a sample of 100 can be considered large in a research project about an organization with 200 employees in total as the target population. Methodological clarity and justification are essential to maintain the rigor of research, not just the inclusion of citations or the use of past studies as templates.
5. The sample size validation procedure can be used to confirm the adequacy of the sample size. This must be done before data collection. Like instrument validation, the adequacy of sample size can be confirmed through experts in the same field. Those with good research and publication experience (3 and more years) with good knowledge of quantitative research methods can be considered experts. Researchers should provide

detailed information about study objectives, research framework, context, unit of analysis, population, availability/unavailability of the sampling frame and other information required by the experts. Research students should document this validation process and keep track of all correspondence (emails, written recommendations, etc.) to support the decision on sample size during the final viva voce. Research supervisors must be informed and kept in loop so they can own such a decision.

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