Data-Driven Approaches to Measuring a *Social Licence to Operate*

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ABSTRACT

Companies in the energy and resources sectors often conduct surveys to understand their acceptance within the community. Such surveys generate rich data, yet sometimes key insights can be missed using conventional plots of average responses for each question. Here, we investigated how multivariate statistics might be used to analyse and communicate information from a Social Impact Assessment of an Australian coal seam gas (LNG) project. The drivers of community acceptance were complex and impacts with the greatest/least average scores were not necessarily those most correlated with acceptance. For example, while housing affordability and availability were consistently seen as negative impacts, individuals' views on employment and economic opportunities were better correlated with acceptance - even though these were, on average, not seen as positive or negative impacts of development. Consistent with previous statistical (path analysis) assessment of the same data, a perceptual map based on r-mode analyses suggested relational factors such as trust and perceptions of good environmental regulation were the most important drivers of acceptance of the LNG industry. Community response maps created using q-mode analyses represented the diversity of opinions for multiple drivers, highlighting that "the community" is not a uniform entity. For example, although those involved in (non-LNG) industry generally reported greater levels of acceptance and trust than others in the community, there were still some individuals within this group that did not trust or accept the LNG industry. While a SLO can be complex and is likely to constantly change, our study shows multidimensional scaling may be a useful tool for communicating social survey results to engineers and managers in a way that encapsulates some of the important details of a SLO, yet still be intuitive enough to include in reporting dashboards.

INTRODUCTION

A 'social licence to operate' (SLO) is critical for companies working in the energy and resources sectors. A SLO is distinct and in addition to a legal licence, but can be enforced by stakeholders through a range of direct and indirect measures that can range up to directly attacking a company's brand and reputation and limiting access to resources, through to indirectly affecting its regulatory licence via legal and political pressure (Gunningham et al., 2004; Thomson & Boutilier, 2011). In turn, such disruption can mean productivity losses, in addition to significant drains on management time (Franks et al., 2014). However, despite an increasing awareness of the importance of an SLO and an apparent willingness to engage with stakeholders (but see Kemp & Owen, 2013), energy and resources companies face difficulty in translating diverse, often unfamiliar information about SLO issues into concrete objectives and corporate strategies.

For any real response by a company, SLO issues will normally need to be brought to the attention of senior management (Franks et al., 2014). While social surveys of stakeholders are commonly used to try to understand and monitor the level of a SLO (Black, 2013; Boutilier, 2011), a key challenge is to present the large amount (and meaning) of social survey data in a way that it is accessible to a company's decision makers; who often have engineering or financial backgrounds and are less familiar with social science research. In practice, social survey data are often collected using Likert scale rating questions such as, "On a scale of one to seven, how much do you accept this company in your region?" or "Rate the impact that this project has had on local employment." Such questions are typically analysed in isolation and then presented as a series of bar charts and means scores that show, for example, that the average level of community support has dropped by 3%, or that 54% of people 'strongly agree' that a project creates jobs. While this approach provides valuable descriptive information, the drivers of community acceptance are complex and often interlinked and cannot be described adequately with simple univariate analyses of each question sequentially. Essentially, the construct of a SLO is multivariate - it depends on a diverse range of factors including the quality of the relationship between the company and community, the impacts and benefits experienced and the attitudes and beliefs of individual stakeholders. Many of these drivers (e.g. procedural fairness, environmental impact) are also latent constructs and can only be measured using multiple questions (Moffat & Zhang, 2014).

Although social issues are often complex, there are several well-established techniques for dealing with the many and multivariate data often collected in social surveys. For example, using factor analysis, Thomson & Boutilier (2011) developed a 15-item survey based on interviews with local community groups that they summarized with factor analysis along four dimensions – economic legitimacy, interactional trust, socio-political legitimacy and institutionalised trust – and then averaged to produce an overall Social Licence score. Moffat & Zhang (2014) followed a different multivariate approach, using path analysis to develop a conceptual model whereby the impacts on social infrastructure, the quality and quantity of contact with the company and procedural fairness affected acceptance of a company's operations, through the mediating factor of trust. While both these examples suggest that quantitative analysis of a social licence using statistical techniques is possible, such analyses may be too complex to communicate quickly within a business operation. Instead, a compromise approach might be one which captures some of the complexity of multivariate data, but presents results in format intuitively accessible to a general audience.

Multidimensional scaling (MDS) is a data exploration approach which can be used to "explore and discover the defining characteristics of unknown social and psychological structures" (Giguère, 2006). It is an established method for analysing and visualising multivariate data and has been used in fields as diverse as psychology (Jaworska & Anastasova, 2009) and biological research (Clarke & Warwick, 2001), often as a complement to more numerical multivariate techniques such as factor and cluster analysis (Jaworska & Anastasova, 2009). The advantage of MDS over other multivariate methods may be summed up by the axiom that ‘a picture is worth a thousand words.’ MDS is essentially a scatterplot technique where correlations across multiple dimensional space are compressed into two (or three) dimensions for visualisation. Thus, the correlations between variables on an MDS plot are represented as the distances between points, with the closer points are to each other the higher their correlation (Borg, Groenen & Mair, 2012).

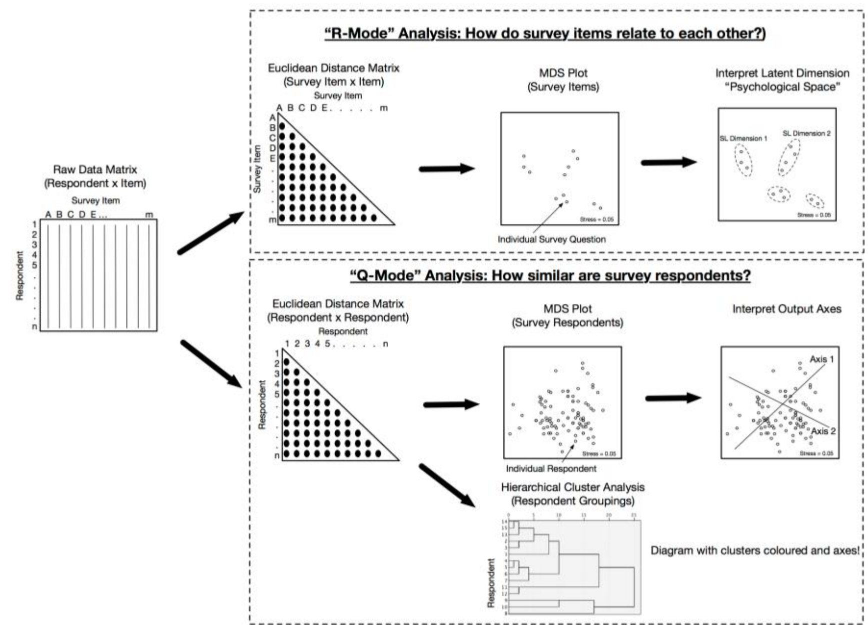

Figure 1 Summary of multidimensional scaling analysis (adapted from Clarke & Warwick, 2001)

The goal of this research was to investigate how multidimensional scaling (MDS) could be used to enhance the analysis and presentation of social survey data, such as that collected to help understand SLO issues in the energy and resources sectors. Specifically, we proposed that MDS could be used to create a visual ‘map’ of the drivers of a SLO that illustrated the interrelations between survey variables and stakeholders, in a format which would be easily accessible to a non-statistical audience.

METHODOLOGY

The present study builds on research by Moffat & Zhang (2014), who used path analysis to assess survey data collected over several years from communities affected by a coal seam gas (CSG) development in rural Queensland, Australia. Details for the survey instrument development and administration used in this paper are as given in Moffat and Zhang (2014), although the analyses in this paper are based on a previously unanalysed third survey from 2013. To initiate our study, we first performed a factor analysis on the 2013 data, confirming the similarity with the previous years and highlighting the same four key factors from previous path analyses – i.e. statements addressed questions of trust, procedural fairness and the quantity and quality of company-community contact. Additionally, extra statements from the 2013 survey on the impacts and benefits experienced by stakeholders and their environmental attitudes were then also analysed. Thirty-one statements on impacts experienced by the community were measured across six categories: water & environment, community safety, social infrastructure, community wellbeing & liveability, local industry participation & training and aboriginal engagement & participation. In each case participants were asked to rate the level of impact they experienced over the previous 12 months on a seven-point Likert scale (1= negative impact, 7 = positive impact). In addition, environmental attitudes were measured by asking participants to rate how much they agreed with seven statements about the company's operations and the local environment: gas as a cleaner source of energy than coal, the company's environmental commitment, the appropriateness of environmental regulations, water management strategies, the relative importance of energy and food security and the ability of CSG to coexist with agriculture.

We first used 'r-mode' analysis (Figure 1, upper panel) to visualise how the community formed judgements about the CSG company's social licence; each point on a 'r-mode' MDS scatterplot represents a survey question, with the distances between points representing their intercorrelations. We expected that this approach would generate a 'perceptual map' that closely resembled the Moffat and Zhang (2014) path analysis model and our first analysis examined the relative importance of the relational drivers of a SLO from this model (trust, procedural fairness etc.), colour coding each of the statements on the plot by the factor they aligned with from the factor analysis. Following this, a second analysis investigated the relative importance of different environmental attitudes and impacts experienced by the community on levels of acceptance.

By contrast, Q-mode analysis (Figure 1, lower panel) represents each survey respondent on the MDS plot, which becomes a form of stakeholder map. Here the goal was to visualise the survey results and identify key groups of respondents based on response profiles on the acceptance, trust and procedural fairness dimensions. We also added axes to these MDS plots, using multiple regression to locate meaningful axes (Borg, Groenen & Mair, 2012). The resultant MDS plot was then used to compare the response patterns of different demographic groups, using examples of gender, occupation and location of residence.

RESULTS AND DISCUSSION

The r-mode 'perceptual map' we created using MDS illustrated how the community formed opinions about the CSG company in a way which was consistent with previous analyses for this community (Moffat & Zhang, 2014). Initially, when we plotted the MDS of the full 16 statements on acceptance and relational factors the statements about contact quantity stood out as a distinct, separate group that were not well correlated with any of the other factors. However, because this this set of three statements stood out as quite different from the other statements including them potentially obscured other meaningful relationships among the other statements. Consequently, we chose to re-run the MDS, excluding the contact quantity statements. This second MDS with the remaining 13 statements led to a more informative plot (Figure 2), with the correlations among colour-coded factors much more obvious than in the initial analysis. Figure 2 also has a low 'Stress' of 0.02 indicating the plot can capture most of the information from a 13 x 13 correlation matrix into a single, two-dimensional map; see also the **Limitations** section below for an explanation of 'Stress' and its importance when interpreting MDS plots (or see Borg, Groenen & Mair, 2012).

Figure 2 (non-metric) MDS representation of the relational drivers of acceptance. Note: Contact Quantity has not been included in this plot in order to increase the resolution of relationships among other survey items

The interpretation of Figure 2 is relatively simple: each point represents a survey item colour coded by factor, with the distance between any two points approximating the correlation between them: the closer the points are to each other, the greater their correlation. For example, Figure 2 shows that survey responses associated with trust were those most correlated with acceptance. In contrast, responses associated with contact quantity were largely uncorrelated with acceptance and in essence located outside the boundaries of Figure 2. Thus, this plot reflects the three key findings from Moffat & Zhang's (2014) path analysis of previous data from the same stakeholder group: trust was the strongest predictor of acceptance, contact quality was more important in building trust than contact quantity, and procedural fairness was a strong predictor of trust - albeit although the reasonably strong correlation is clear, the directionality of relationships tested via path analysis is not obvious in the MDS.

Respondents were asked also asked about their environmental attitudes and the impacts experienced from the CSG company's operations. Initially all 31 impacts were subjected to MDS, resulting in a moderately higher 'Stress' value of 0.16 (suggesting that the plot does not adequately capture the multivariate relationships well in two dimensions). Four impacts contributed disproportionally to the overall stress and were therefore excluded in a subsequent re-run of the MDS, such that Figure 3 depicts the MDS from a correlation matrix containing 27 impacts and 13 relational variables (and a lower 'Stress' = 0.12).

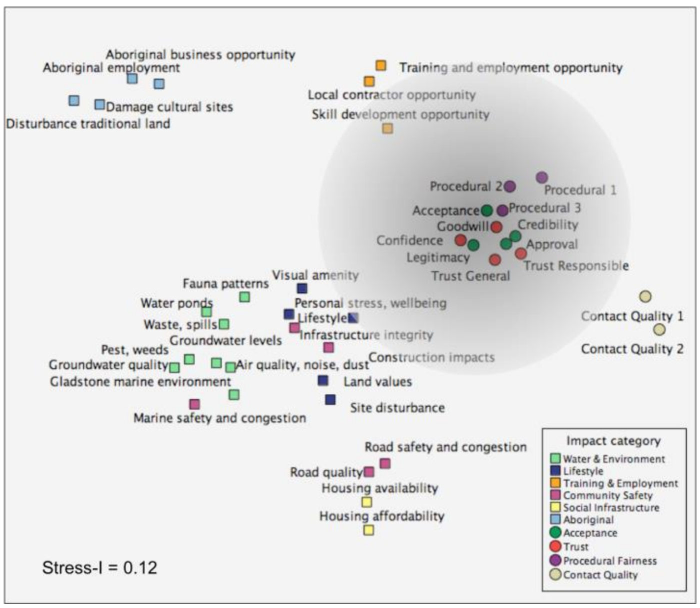

Figure 3 MDS map showing the relative importance of relational (circles) and environmental (squares) drivers

The dark cloud in Figure 3 has no formal statistical meaning but has been added to help highlight which drivers were the most important in this survey set. The most important drivers lay within the 'local industry participation & training' and 'lifestyle' clusters, while the least important concerned housing and aboriginal engagement. It also illustrated that trust and procedural fairness were more important drivers than any of the local impacts experienced. This suggests that the negative impacts reported by the community may be symptoms of underlying relationship issues, rather than important drivers of a SLO *per se*. For example, it may be easier to express concern about tangible impacts like dust or housing affordability than it is to raise 'soft' relational issues such as trust or fairness. Parsons & Moffat (2014) reached the same conclusion from interviews with stakeholders, finding that the 'relational narrative' was at least as important as the 'impact narrative.' Yet as discussed by Moffat and Zhang (2014), this runs counter to the common 'Social Licence' practice of many companies, who often focus predominantly on mitigating operational impacts.

In both 'r-mode' examples, the MDS map shows which community drivers and attitudes are important – and, by extension, possibly where to focus community engagement and public relations strategies. Potentially, this sort of diagram can be thought of as providing summary maps of the issues affecting (and not affecting) the company's SLO with these stakeholders, in a way that should be intuitive to decision makers (Borg, Groenen & Mair, 2012)

'Q-mode' MDS was then used to analyse demographic response patterns, by superimposing relevant demographic variables onto the plot; for each of the three cases examined here only the demographic coding was changed and the underlying MDS scatterplot remained constant. Figure 4.A illustrates that females formed a large proportion of those extremely opposed to the project and males a greater proportion of those with high acceptance. Although a simple univariate analysis of gender/acceptance would likely also indicate this, the MDS allows the different response patterns for males and females across multiple dimensions simultaneously to be assessed, leading to greater insight into potential mechanisms. For example, Figure 4.A suggests that females rated the company more negatively overall, particularly along the trust and procedural fairness dimensions.

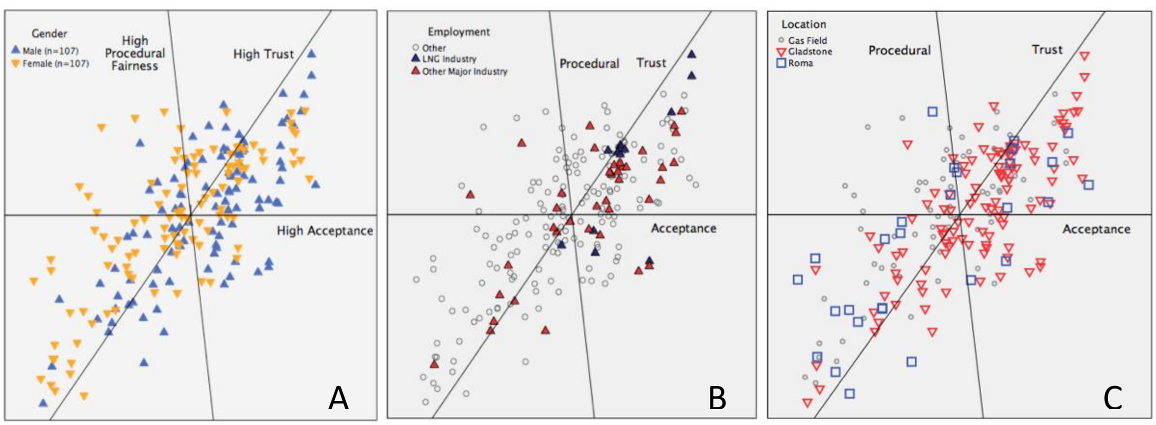

Figure 4 MDS plot superimposed with A) gender; B) the employment category; and c) residence location of survey respondents

Similarly, the responses of stakeholders who worked in other major industry and LNG employee categories suggested a dual narrative about the CSG company's regional acceptance with those working in industrial enterprises in a regional area (Figure 4.B). Perhaps most importantly, there appeared to be a few employees within the LNG industry with moderate to low levels of acceptance, but who also registered lower on procedural fairness and trust; presumably, these people are unlikely to be advocating for their employer within the community. There was also a clear geographical difference, with respondents in Gladstone generally more supportive than the average, but also forming a large proportion of reporting low procedural fairness but high acceptance (Figure 4.C). All three examples illustrate how a MDS map can represent the complex structures of survey results in a format that can be readily understood, while allowing the researcher to visually compare different groups across multiple dimensions simultaneously.

Limitations

While we have illustrated that MDS can be ideally suited for data exploration and visualization of the drivers of a SLO, results should be always interpreted critically and wherever possible considered against the input proximity matrix and/or validated against other multivariate techniques. It is important to remember that the relative distance between points on a two dimensional plot necessarily depends on the construction of the proximity matrix and the ability of the MDS algorithm to find a solution to summarise as much of the multivariate relationships as possible into two dimensions. Consequently, the distances and relationships among points on a plot need to be interpreted in a relative sense (e.g. ‘A’ is more closely correlated with ‘B’ than ‘C’) and changes to the dataset and/or similarity measures can potentially make a large difference to the appearance and how plots are then interpreted. MDS is also not a statistical test *per se* and the interpretation of MDS plots can be quite subjective. Similarly, there are only ‘rules of thumb’ about what is or is not an adequate level of ‘Stress’ and thus any decision about whether a solution is an adequate representation of the complexity of the data involves a large element of judgement (Borg, Groenen & Mair, 2012). MDS that include variables which do not represent a consistent system of community beliefs (including unrelated variables) can potentially distort the relative positions of points and interpretability of the results. So, it is always necessary to check the Stress contributions of individual points and it may be necessary to limit the number of or omit specific variables to obtain a meaningful analysis (as we did in both of our r-mode examples). Thus, for examining SLO issues, the methodology is best considered as a complement to other developing modes of analysis, such as factor analysis (Boutilier, 2011) or path analysis (Moffat & Zhang, 2014).

CONCLUSION

This paper highlights MDS as an additional tool for practitioners and researchers interested in monitoring and understanding what drives a SLO. The example here was specifically for communities affected by CSG development in Australia, but MDS could be applicable for almost any developments where social survey data are collected, particularly where large sets of variables are collected and need to be summarised in an intuitive way that still reflects some of the complexities of the underlying data. This paper also adds to a small but growing body of literature demonstrating the use of multivariate analysis in the SLO domain. Together, this work suggests that an empirical, data-driven approach to measuring a SLO is possible, which might lead to evidence-based improvements in company decision making processes. This work illustrates how theoretical and conceptual models can be combined with quantitative measurement and analysis in a way which could progress social reporting towards the same level of sophistication as environmental and financial reporting. This in turn, could lead to better industry management of SLO issues and potentially create better outcomes for both the company and community.

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REFERENCES

Black, L.D. (2013) *The Social Licence to Operate: Your Management Framework for Complex Times*. Do Sustainability, Oxford, UK.

Borg, I., Groenen, P., Mair, P. (2012) *Applied multidimensional scaling*, Springer, New York.

Boutilier, R., (2011) *A Stakeholder Approach to Issues Management*. Business Expert Press, LLC, New York.

Clarke, K.R., Warwick, R.M. (2001) *Change in marine communities: an approach to statistical analysis and interpretation*. PRIMER-E Limited Plymouth, UK.

Franks, D.M., Davis, R., Bebbington, A.J., Ali, S.H., Kemp, D., Scurrah, M. (2014) Conflict translates environmental and social risk into business costs. *Proceedings of the National Academy of Sciences of the United States of America (PNAS)*, 111(21), 7576–7581.

Giguère, G. (2006) 'Collecting and analyzing data in multidimensional scaling experiments: A guide for psychologists using SPSS', *Tutorials in Quantitative Methods for Psychology*, 2, 26–37.

Gunningham, N., Kagan, R.A., Thornton, D. (2004) 'Social License and Environmental Protection: Why Businesses Go beyond Compliance', *Law & Social Inquiry*, 29, 307–341.

Hair, J., Black, W., Babin, B., Anderson, R. (2010) *Multivariate Data Analysis*, 7th Edition, Pearson Prentice Hall, Essex, UK

Jaworska, N., Anastasova, A.C. (2009) 'A review of multidimensional scaling (MDS) and its utility in various psychological domains'. *Tutorials in Quantitative Methods for Psychology*, 5, 1–10.

Kemp, D., Owen, J.R. (2013) 'Community relations and mining: Core to business but not "core business"' *Resources Policy*, 38, 523–531.

Moffat, K., Zhang, A. (2014) 'The paths to social licence to operate: An integrative model explaining community acceptance of mining' *Resources Policy*, 39, 61–70.

Parsons, R., Moffat, K. (2014) 'Integrating impact and relational dimensions of social licence and social impact assessment', *Impact Assessment and Project Appraisal*, 32, 273–282.

Thomson, I., Boutilier, R.G. (2011) 'Social license to operate' in: *SME Mining Engineering Handbook*, 3rd Edition, Society for Mining, Metallurgy, and Exploration, 1779–1796.