Framework for mining community consultation based on discrete choice theory

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Abstract: The significance of local community acceptance to the success of a mine cannot be over-stated. Project sustainability has implications for local community acceptance as the development and operation of a mine can be viewed as a development intervention with concrete social, economic and environmental impacts. Although, some work has been done to understand these relationships, very little has been done to quantitatively model the relationship between project sustainability and community preferences. This paper presents a framework for quantitative community consultation for mining projects based on discrete choice theory. The paper establishes the most appropriate choice model and uses a review of the literature to select key determinants of mining community acceptance. Recommendations are made for future research to implement the proposed framework. This framework will allow engineers and regulators to better evaluate community input.

Keywords: mining; sustainable development; discrete choice model; community consultation; community acceptance.

Reference to this paper should be made as follows: Que, S. and Awuah-Offei, K. (2014) 'Framework for mining community consultation based on discrete choice theory', *Int. J. Mining and Mineral Engineering*, Vol. 5, No. 1, pp.59–74.

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1 Introduction

Local community acceptance of resource projects is important for successful permitting and operation of these projects. The community's support or opposition is critical in obtaining permits prior to commencing mining. In fact, in some jurisdictions (e.g., Peru) community acceptance has been included as a requirement for permitting. In the United States (USA), as in most other countries, community consultation is required during environmental impact assessment although the community's acceptance is not necessarily a requirement for granting a permit. A good illustration of the importance of community acceptance during permitting is Newmont Mining's Minas Conga copper and gold mine in Peru, which was halted in 2012 due to opposition from local residents worried about water pollution (Anonymous, 2012). This was largely due to the limited scope of community consultation during the early stages of the project. During mining or project execution, local community acceptance still plays an important role. Safe and smooth operation, devoid of protests (both at mine sites and annual general meetings) and vandalism, which can lead to denial of mine access and shut-downs, depend on community acceptance. Sustainability impacts (perceived and real) of a mine during operation affects community acceptance. A mine, after all, is a development intervention with sustainable development implications.

Sustainable development is defined as the ability of current generations to meet their needs without compromising the ability of future generations to meet their own needs (Brundtland, 1987). It is well established that this includes social, economic and environmental impacts – the so called triple bottom line (Munashinge and Shearer, 1995). Mining has social, economic, and environmental impacts – both positive and negative. There is an inter-relationship between the support, or lack thereof, from the local community and the sustainable development impacts of mining. The mining project produces social, economic, and environmental impacts as well as affects several demographic aspects of the geographic area.

There is a need for community engagement throughout the mine life cycle (exploration, development, exploitation and closure) to ensure sustainable development of the region that hosts the mine. This need is widely accepted. However, in practice, community consultation processes vary widely among companies, jurisdictions, and countries. It is mostly qualitative in nature and relies, mostly, on voluntary participation from stakeholders. However, qualitative community consultation alone may not provide enough input/feedback on the community's needs and level of acceptance. For instance, Newmont Mining engaged in significant community consultation on the failed Minas Conga project.

There has been very little research, beyond qualitative linkages, done to understand the determinants of community acceptance. Discrete choice theory, based on the Nobel winning work by McFadden (1974), has been successfully used in econometrics and other disciplines to understand consumer behaviour, among others. For example, choice theory has been used to evaluate community acceptance of renewable energy projects (Dimitropoulos and Kontoleon, 2009). This provides a framework to objectively and quantitatively understand the characteristics of mining projects and demographic factors that are determinants of community acceptance. Choice theory will facilitate data-driven community consultation if properly applied to mining. The goal of current research by the authors is to facilitate improved community consultation by providing further insight

on the determinants of local community acceptance using discrete choice theory. The objectives of this paper are to present:

- results of a comprehensive literature review
- a proposed research framework for mining community consultation.

This was done by reviewing peer-reviewed journal papers to analyse relevant choice models and key attributes of mining projects. The results of the analysis are used to propose a framework for future research on community acceptance of mining.

This work will be a significant contribution to knowledge and the literature on sustainable mining. The research will provide needed insight for mining professionals and government regulators to facilitate meaningful community consultation. This work provides the basis for planned future work that will result in a framework to incorporate community acceptance considerations in mine planning and design.

2 Determinants of community support of mining

The key factors that determine (determinants) the level of community support (say percentage of the population in favour of the mine) of a mining project can be classified into two groups:

- characteristics and impacts of the mine
- demographic factors.

2.1 Sustainable development impacts of the mine

Building and operating a mine is a developmental intervention with significant sustainable development implications. Over its life cycle, a mine will have significant but varying social, economic and environmental impacts. Table 1 summarises the sustainable development impacts of mining with examples of specific impacts. The environmental impacts are well known among the general populace, although they may be under- or mis-informed on some aspects. However, the social and economic impacts are not that obvious to many people, even if they know of these linkages. These impacts (real or perceived) have an impact on local community support. Again, the Minas Conga case in Peru is a clear example of how mine sustainability impacts (in this case impacts on water) can affect community support.

2.2 Demographic factors

Various demographic factors have been shown to affect an individual's or a household's likelihood to support (proposed) mining in their community. For instance, Ivanova and Rolfe (2011) show that gender, number of children, and age significantly ($p < 0.05$) affect community support. Other factors include household income (Petkova et al., 2009), buffer from the mine (del Rio and Burguillo, 2008; Ivanova and Rolfe, 2011) and perceived or actual net gain from project (del Rio and Burguillo, 2008).

It has long been posited that one of the key motivations for human decisions is utility maximisation (say, in consumer behaviour). Thus, the authors postulate that utility

maximisation is the framework to understanding individual/household support, or lack thereof, of mining. Any demographic factor, which significantly affects the utility function, will be a determinant of community support.

Table 1 Examples of sustainable development impacts of mining

Impact	*Examples*
Environmental	
Material and resource consumption	US surface coal mining consumes 7.8 to 9.4 kg Sb-eq./tonne of coal (Ditsele and Awuah-Offei, 2012)
Air emissions	
Water pollution	>11,500 miles of streams have been disturbed/impacted by coal mining (OSMRE 1978–2008)
	>23,000 km of streams are affected by acid mine drainage from mines (Kim et al., 1982; USFS, 1993)
Land use impacts	>1.5 million acres of land have been disturbed/impacted by coal mining (OSMRE 1978–2008)
Noise	
Social	
Human rights	
Working conditions	
Health and safety	Migration into mining towns (often higher male migration) can stress local services and lead to health problems, such as HIV-AIDS (Hunter, 2007; Petkova et al., 2009)
	Influx of itinerants lead to crime and impacts on community identity (Petkova et al., 2009)
Cultural heritage	
Governance	
Socio-economic repercussions	
Economic	
Job creation	US mining supports nearly 1.98 million jobs (NMA, 2012)
	In rural economies, mining often creates more jobs than the population can take (Petkova et al., 2009)
Taxes	US mining generated $50 billion in federal, state and local taxes in 2010 (NMA, 2012)
Downstream effects	Petkova et al. (2009) reports that nearly all business respondents in a survey administered (in rural Australia) reported a generally positive impact on their business since the coal mining boom

2.3 Discussion

It is clear from the work cited in this section that:

- mining contributes to sustainable development (positively and negatively)
- demographic factors do affect community acceptance.

The linkage between environmental impacts and community support has long been accepted. The example of the Minas Conga project, previously cited is one example among many (Anonymous, 2012). But the connection between the social and economic impacts have not been discussed that much. However, the literature supports this connection too. For example, Petkova et al. (2009) shows that employment opportunities, increase in local business opportunity, the influx of itinerants, and community identity were all important to local residents in determining community acceptance. We, therefore, draw the motivation from the literature for one of the key hypothesis in this research: *project sustainability is a key determinant of community acceptance*.

This hypothesis needs to be rigorously tested with further research. The other question that arises from this is: which sustainability impacts of a mining project are critical determinants of community acceptance? Are impacts on employment more important than environmental impacts? Are contributions to the local tax base and economic development more important than the social ills associated with migration? These questions need good objective answers that further research, using decision theory, can provide.

Based on a critical review of the literature the authors propose the list of mine attributes in Table 2 as the preliminary list of factors that influence community support. This list provides a basis for conducting research on what are the key determinants. Such research will rank the list in Table 2 on importance and their inter-relations.

Table 2 Attributes of mining projects that are determinants of community acceptance

Determinant	*Reference*
Social	
Population changes	Ivanova and Rolfe (2011) and Petkova et al. (2009)
Infrastructure improvement (transportation, education, human services, internet, hospital, and shopping)	Ivanova et al. (2007) and Petkova et al. (2009)
Cultural impacts	Lockie et al. (2009) and Petkova et al. (2009)
Traffic and crime increase	Lockie et al. (2009) and Petkova et al. (2009)
Economic	
Job opportunities	Ivanova et al. (2007)
Income increase	Ivanova et al. (2007) and Petkova et al. (2009)
Cost of housing or housing shortage	Ivanova et al. (2007) and Petkova et al. (2009)
Labour shortage for other business	Petkova et al. (2009)
Environmental	
Noise pollution	Petkova et al. (2009)
Water shortage or pollution	Petkova et al. (2009)
Air pollution	Petkova et al. (2009)
Land pollution	Lockie et al. (2009)

Table 2 Attributes of mining projects that are determinants of community acceptance (continued)

Determinant	*Reference*
Management and others	
Decision making mechanism (EIA, Referendum, Negotiation, or combination)	Muradian et al. (2003)
Independent and transparent information	Muradian et al. (2003)
Mine buffer (distance of residence from mine)	Ivanova and Rolfe (2011)
Mine life	Ivanova and Rolfe (2011)

3 Discrete choice theory and modelling

Discrete choice analysis can be employed to describe the influence of the characteristics of decision makers and the attributes of alternatives and choices. The most popular discrete models are multinomial logit (MNL), multinomial probit (MNP), nested logit (NL), and mixed multinomial logit (ML) models. While the NL model is widely used in different fields, it is not discussed in this paper since mining acceptance is not a 'nested' problem. Discrete choice theory and the other three models are discussed separately in the following.

3.1 Discrete choice theory

The basic theory of discrete choice modelling is random utility maximisation (Marschak, 1959). The individual decision maker's overall preference of a choice alternative is a function of the utility, which the alternative holds for the individual. This individual's utility (U_{ni}) for an alternative is separable into two components, as shown in equation (1):

- the component which can be explained by the observed (by a researcher) variables
- the component, which can be explained by unobserved variables – often, deemed random.

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

U_{ni}: Utility of alternative i to individual n

V_{ni}: Observed component measured for alternative i of individual n

ε_{ni}: Unobserved random component.

It is postulated that an individual will prefer the choice alternative perceived to have the greatest utility. If individual n prefers the mining project or plan i of choice set J, the probability is:

$$\begin{aligned} P_{ni} &= \text{Prob}(U_{ni} \geq U_{nj}, \quad \forall i \neq j, \quad i \text{ and } j \in J) \\ &= \text{Prob}(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}, \quad \forall i \neq j, \quad i \text{ and } j \in J) \\ &= \text{Prob}(\varepsilon_{ni} + \varepsilon_{ni} \geq V_{nj} + V_{nj}, \quad \forall i \neq j, \quad i \text{ and } j \in J). \end{aligned} \tag{2}$$

3.2 Multinomial logit model

The multinomial logit model (MNL) was first formulated by McFadden in the 1970s (McFadden, 1974). The observed component V_{ni} is a linear function of X_{ni} (a vector of observed variables that relate to the alternative and/or the decision maker) and the random component (ε). The error terms, ε, are assumed to be independently and identically distributed (iid) with type 1 extreme value distribution.

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta_n' X_{ni} + \varepsilon_{ni}. \tag{3}$$

β_n is the vector of coefficients of variables for person n representing that person's taste.

The cumulative distribution function (cdf) of ε is given by equation (4).

$$F(\varepsilon_{ni}) = \mathrm{e}^{-\mathrm{e}^{-\varepsilon_{ni}}}. \tag{4}$$

The probability of choice i to individual n is:

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})}. \tag{5}$$

The multinomial logit (MNL) model is widely used in different fields (Cho, 1997; Walekhwa et al., 2009; Kwak and Clayton-Matthews, 2002). However, MNL model has three main shortcomings. First, the coefficient vector β_n is fixed in an MNL model. This means different people with the same surveyed characteristics will make the same choice given the same choice set. Actually, even twins might make different choices. Thus, the fixed coefficient β_n is not reasonable. Second, the MNL model has an independence of irrelevant alternatives (iia) property, since the error terms, ε_n, are assumed to be independently and identically distributed (Train, 2009). The probability ratio of i and k only depend on the alternatives i and k in the MNL model and it is not relative to other alternatives (equation (6)).

$$\frac{P_{ni}}{P_{nk}} = \frac{\exp(V_{ni}) \Big/ \sum_{j=1}^{J} \exp(V_{nj})}{\exp(V_{nk}) \Big/ \sum_{j=1}^{J} \exp(V_{nj})} = \exp(V_{ni} - V_{nk})^{-1}. \tag{6}$$

The iia property means that there is no cross elasticity among the alternatives. If an attribute of one alternative j is changed, the changes of other alternatives' probabilities are not relative to the changed alternative j. Yet, this is not true in some choice situations. For example, assume there are three kinds of vehicles in a market: large gasoline cars, small gasoline cars and small electric cars. Their current market shares are 66%, 33% and 1%, respectively. Also, assume that a government subsidy increases the market share of the small electric car from 1% to 10%. Using the MNL model, the market share of the other two cars would be predicted to drop while still maintaining the same ratio. The market share of large gasoline cars would drop from 66% to 60%, and that of small gasoline cars would drop from 33% to 30% (maintaining the 2 : 1 ratio). The ratio of the market share of these two vehicles have to be 2 : 1 since their utility rate is 2 : 1, and is not relative to any other alternatives. However, this prediction is unrealistic. Since the electric car is small, subsidising it can be expected to draw more from small gas cars than from large gas cars.

Thirdly, the MNL model has the potential to capture dynamics of repeated choice. But the repeated choice has to be independent over time since the error terms, ε_n, are assumed to be independently and identically distributed (iid) in the MNL model. Thus, the MNL model cannot handle repeated choice situations if they are correlated over time.

3.3 Multinomial probit model

The first binary probit model was derived by Thurstone (1927). Hausman and Wise (1978) and Daganzo (1979) employed and developed it for choice behaviour. The utility equation is the same as the MNL model (equation (3)), but the ε_{ni} are assumed to be normally distributed with mean zero and covariance matrix Ω.

The probability density function (pdf) of ε_n is:

$$\Phi(\varepsilon_n) = \frac{1}{(2\pi)^{\frac{1}{2}} \mid \Omega \mid^{\frac{1}{2}}} \exp\left(-\frac{1}{2}\varepsilon'\Omega^{-1}\varepsilon_n\right) \tag{7}$$

ε_n' is a vector of ε_{ni}, and $\varepsilon_n' = (\varepsilon_{n1}, \varepsilon_{n2}, \ldots, \varepsilon_{nJ})$.

For individual n, probability of choice i, is:

$$\begin{aligned} P_{ni} &= \text{Prob}(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}, \quad \forall i \neq j) \\ &= \int I(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}, \quad \forall i \neq j)\Phi(\varepsilon_n)\, \mathrm{d}\varepsilon_n. \end{aligned} \tag{8}$$

$I(\bullet)$ is an indicator function: it equals 1 when the expression inside the parenthesis is real and 0 otherwise.

Compelling progress was made by Haaijer et al. (1998). They accounted for random variation in the coefficients β over decision-makers, instead of being fixed as before. The coefficients β were assumed to be normally distributed in the population with mean b and covariance W. And the parameters b and W can be estimated by a model.

Thus, the three limitations of the MNL model are all relaxed in the MNP model. Firstly, two people who have the same surveyed characteristics can make different choices since there is a covariance W between the normally distributed coefficients, β_n. Secondly, MNP does not have the iia property and represents any substitution pattern, because ε_n are assumed to be normally distributed with mean 0 and covariance matrix Ω. In the previous example, the large gasoline and small gasoline cars' market shares would not have to maintain the 2 : 1 ratio after the small electric car's market share changes. Their market share will be relative to the change in small electric car's market share. Finally, the MNP model can handle repeated choice situation where choices are correlated over time by expanding the covariance matrix Ω of the errors ε_n. The details are not explained here since the current research does not include dynamic choice modelling of mining local community acceptance.

3.4 Mixed multinomial logit model

The mixed multinomial logit (ML) model was proposed by McFadden and Train (2000). In the ML model, the distribution of coefficents, $f(\beta)$, is not limited to the normal distribution like in the MNP model. The ML model can utilise any distribution for the

random coefficients. The most popular distributions of the random parameters are uniform, triangular, normal and lognormal distributions.

Mixed logit probabilities are the integral of standard logit probabilities over the coefficents distribution function, $f(\beta)$.

$$P_{ni} = \int L_{nj}(\beta) f(\beta)\, \mathrm{d}\beta. \tag{9}$$

$L_{ni}(\beta)$ is the logit probability evaluated at parameters β

$$L_{nj}(\beta) = \frac{\exp\left[V_{nj}(\beta)\right]}{\sum_{j=1}^{J} \exp\left[V_{nj}(\beta)\right]}. \tag{10}$$

Then,

$$P_{nj} = \int \frac{\exp[V_{nj}(\beta)]}{\sum_{j=1}^{J} \exp[V_{nj}(\beta)]} f(\beta)\, \mathrm{d}\beta. \tag{11}$$

McFadden and Train (2000) show that any choice model can be approximated by the ML model with appropriate specification of the observed variables and distribution of coefficients. The MNP is a special case of the ML model where the coefficent distribution function, $f(\beta)$, is a normal distribution.

3.5 Discussion

The multinomial logit (MNL) model has been used to understand the decision-making process of local communities regarding preferred mineral project development choice (Ivanova et al., 2007; Ivanova and Rolfe, 2011). However, their work did not aim to determine the effect of sustainability on community acceptance, which affected the choice of mining attributes included in the model. Also, their model had a high alternative specific constant (Ivanova et al., 2007) or low R^2 (0.148) (Ivanova and Rolfe, 2011). This is because they tracked very few attributes of mining (as indicated by the high alternative specific constant). Also, they employed an improper model.

The MNL model is not suitable for mining local acceptance due to the first two limitations: fixed taste coefficient β_n and iia property. Fixed taste coefficient is unsuitable for mining community acceptance modelling. In local mining community acceptance modelling, it is not possible to include all demographic factors (due to survey and data limitations). This means people/households with the same surveyed demographic factors will have the same characteristics. However, it is not reasonable to expect that all individuals/households with the same surveyed characteristics will make the same choice (they are still different in other ways). Thus, we have to appreciate the effect of unobserved variables. And the model needs to allow preferences to vary with the observed variables and randomly. Yet, the MNL model restricts one attribute to one fixed coefficient, which is a limitation for this application.

Additionally, the iia property is not true for some mining local acceptance choice situations. Consider the choice set presented in Table 3, for example. Assume that 66%, 33% and 1%, respectively, choose options 1, 2, and 3. Assume also that after public

education, more people have been convinced of the ability of the mining company to implement the proposed 3 : 1 wetland compensation plan (i.e., 3 acres of wetlands will be built elsewhere for every acre of wetlands impacted), leading to an increase in the percentage of people in favour of Option 3 to 10%. The MNL model (with the iia property) will predict proportional decreases in Options 1 and 2 to 60% and 30%, respectively (same as the previous example). However, it is likely that more of those in favour of Option 1 (those influenced mostly by wetland concerns) will change their mind with this change than those who were in favour of Option 2 (wetlands were not an issue for those).

Table 3 Sample choice set

Choice options	*Acres of wetlands impacted by mine*	*New jobs created*
Option 1	0	500
Option 2	1000	500
Option 3	1000	1000

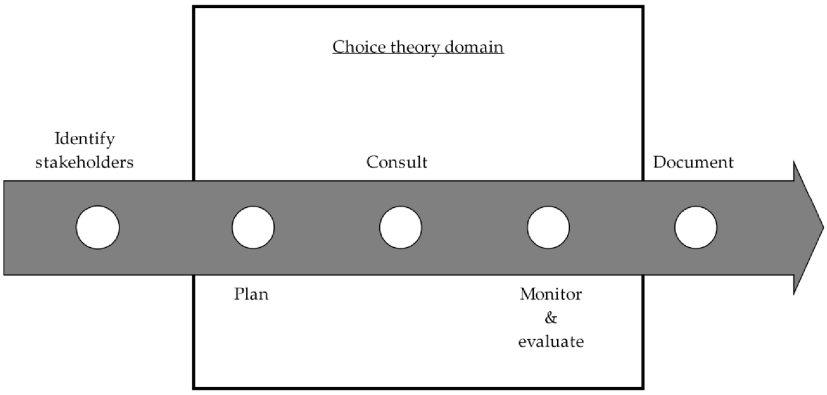
These two constraints (constant β_n and iia property) are relaxed in the mix multinomial logit model. Also, the ML model allows each random coefficient to follow any distribution (instead of being restricted to the normal distribution as in the MNP model), which should be realistic in a complex situation such as mining community acceptance. Additionally, the ML model has the potential to handle repeated choice situations, even if the repeated choice is correlated over time. The ML model will still be suitable for dynamic mining local acceptance model if we choose to do it later. Thus, we posit that the mix multinomial logit model should be the most appropriate one for mining local acceptance model.

4 Proposed framework for mining community consultation

4.1 Proposed public consultation process

This work proposes a new framework for mining community consultation based on discrete choice theory. Historically, the mining industry has approached the consultation process by making mine development plans, assessing impacts, and then defending the assumptions and plans through community consultation. This approach has been found to be deficient and categorically classified as anything but consultation (Thomson and MacDonald, 2001). The contemporary view of public consultation is that it is a management tool to engage stakeholders in decision making throughout the mine life cycle (IFC, 1998; Joyce and MacFarlane, 2001; Thomson and MacDonald, 2001). The International Council on Mining & Metals (ICMM) recommends a five-step process, which includes stakeholder identification, consultation planning, consultation, monitoring and evaluation, and documentation – Figure 1 (ICMM 2013).

Figure 1 Community consultation process



Source: Adapted from ICMM (2013)

As shown in Figure 1, choice theory (choice modelling and surveys) can be useful within steps 2–4. Discrete choice theory can provide quantitative feedback on:

1 preferred development options

2 willingness-to-pay for options

3 important attributes of options for community (stakeholder) support/acceptance

4 important demographic factors for community (stakeholder) support.

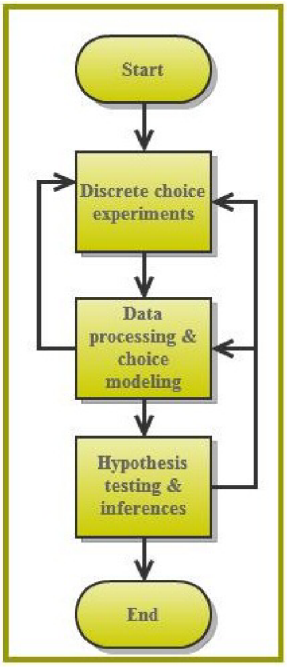
ICMM (2013) recommends using different consultation methods of increasing complexity and cost for increasing impact and influence, depending on context. During stakeholder identification, data on key demographic factors from discrete choice modelling can be useful in identifying stakeholders. Stakeholder consultation with discrete choice modelling will provide quantitative information on community preferences beyond what is in the plan (i.e., the data provides insight beyond accept or reject the proposed development options). Perhaps, the most beneficial aspect of discrete choice theory in community consultation is the use in monitoring and evaluation. This is due to the fact that discrete choice modelling provides quantitative data on the results as well as the uncertainty surrounding the estimates. The uncertainty estimates can help diagnose wrong feedback due to limited survey respondents from particular stakeholders, etc.

4.2 Research needs

However, in order to incorporate discrete choice theory into mining community consultation further research is necessary. The authors propose research based on the approach shown in Figure 2, which they are currently undertaking. This research will extend discrete choice theory to mining community consultation and provide baseline choice data, which individual campaigns augment. The approach is to design and administer discrete choice experiments to representative samples in various communities to acquire data for choice modelling. The data from these choice experiments will then be used to determine the mixed multinomial logit model parameters. The modelling results

will be used then to test the research hypotheses. Since the surveys (choice experiments) will be done in the selected communities sequentially, feedbacks from the earlier stages (choice modelling and hypothesis testing) will be incorporated into the latter sages (Figure 2).

Figure 2 Proposed research flow chart (see online version for colours)



The first task (beyond literature review) is to conduct choice experiments, which will provide the data for discrete choice modelling. The research team will use established best practice to design and administer the questionnaires (Louviere et al., 2000; Hoyos, 2010). In order to test the research hypothesis (*project sustainability is a key determinant of community acceptance*), the set of variables included in the choice alternatives need to include mining sustainability impacts (Table 1).

The challenge is to limit the number of variables to only the most important variables (e.g., Table 4). The literature shows that the cognitive burden (the cognitive requirements of the choice decision) increases with the complexity of the choice decision (Caussade et al., 2005; Hoyos, 2010). This can lead to a gap between the cognitive ability of respondents and the cognitive burden of the decision they are asked to make. This can be avoided by using focus groups and pilot surveys (Hoyos, 2010). The second challenge in the choice experiment design is determining the appropriate levels, which the included variables can be set, to generate the choice alternatives. Expert opinion will be sought to determine appropriate levels. These will also be tested in the focus groups and pilot surveys (Louviere et al., 2000).

Table 4 Mine development characteristics and levels used by Ivanova and Rolfe (2011)

Variable	*Levels*
Additional annual costs to household	$0
	$250
	$500
	$1000
Housing and rental prices	25% increase
	No change
	25% decrease
Level of water restrictions	Some for households, town parks and gardens are drier than now
	None for households, town parks and gardens are drier than now
	None for households, town parks and gardens are greener than now
Buffer for mine impacts close to town	Moderate impacts from noise, vibration and dust
	Slight impacts from noise, vibration and dust
	No additional impacts
Population in work camps	No more housing and 5000 in work camps
	1000 in housing and 4000 in work camps
	4000 in housing and 1000 in work camps

The second task is data processing and model fitting. Although, the authors postulate that the mixed multinomial logit model is best suited for the mining community acceptance problem, the intent is to fit the MNL and MNP models to the data as well. Thus, the results of different models can be compared to verify the deduction that the ML model is the most suitable model. Best practices for model goodness-of-fit will be followed (Louviere et al., 2000; Hoyos, 2010). The goodness of fit of estimated choice models is usually measured by likelihood ratio index (LRI) or pseudo-rho squared. The LRI is zero if the model is no better than no model and one if it perfectly predicts each choice. A rule of thumb is to accept models with LRI greater than 0.2 (Hoyos, 2010).

Testing the research hypothesis is the final part of this research. The goodness-of-fit tests used for choice model fitting provide tests of statistical significance. The results provide the coefficients and the significance level of each factor (variable) in the model. To test the hypothesis that mining project sustainability is a key determinant, all related variables will be examined for their significance (say, at $\alpha = 0.05$). By the same logic, we would evaluate the significance of demographic factors to test the hypothesis that demography is a key determinant of community acceptance.

Sustainability assessment and evaluation has evolved over the last decade. Community consultation is now seen as a crucial part of sustainability assessment. However, in most cases, the community is presented with a project to accept or reject. The community consultation process often leads to changes in the mine (project) plan. However, the changes can sometimes ignore major concerns and do not address 'willingness-to-pay', a key criterion for consumer behaviour, for instance. What is the community willing to give up for their preferred mine (project) plan? This approach requires a comprehensive discussion of sustainability (environmental, social, and

economic impacts) as well as demographics. Discrete choice theory provides the framework to handle all these issues to facilitate useful and meaningful community consultation.

The current research effort will provide insights into these critical issues. These insights will be beneficial for both regulators and mining professionals. The proposed research framework will provide objective assessment of the factors affecting local community acceptance of resource (energy) projects. Further research, beyond what is proposed in this paper, will develop a framework that helps mine planning engineers to design mines in the context of sustainability (including the effect of community acceptance). The ultimate goal is to facilitate design in the context of sustainability (Fletcher and Dewberry, 2002).

5 Conclusions

Community consultation is important for mining project sustainability and success. The literature shows a clear interaction between community support and sustainability. Measurable demographic factors have been shown to affect community acceptance. Research using choice theory to understand mining community support is minimal: only two examples (in the same communities by the same researchers) were found in this literature survey (Ivanova et al., 2007; Ivanova and Rolfe, 2011). These examples appear not to have tracked the most significant attributes of mining development options (high alternative specific constant or low adjusted R^2). This review also shows the multinomial logit model may not be the most appropriate for mining community acceptance.

This paper proposes a framework for including choice theory into mining community consultation. Further research, based on choice experiments and mixed multinomial logit modelling, is proposed to facilitate this. The work will include significant sustainability (environmental, social, and economic) attributes of mining in choice experiments to be administered in several communities. The authors propose to use focus groups and expert opinion to limit cognitive burden in the choice experiments, while including the most significant attributes and demographic factors. The results of the modelling will be used to test the hypothesis that project sustainability is a key determinant of community acceptance.

This work will provide significant insights for regulators and mining professionals and transform current community consultation practices. The authors recommend that future research (beyond what is covered in this paper) needs to concentrate on how to use results of choice experiments and modelling to make a shift from the current mine planning and design framework to one where sustainability is the context for the design.

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