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Factors Influencing the Success of Culturally and Linguistically Diverse Students in Engineering and Information Technology*

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The perception of supervisors who supervise culturally and linguistically diverse (CALD) higher Degree research students (HDR) in Engineering and IT was analysed to identify, operationalise and quantify factors which could influence outcomes related to successful completion of HDR studies. A large study was conducted from three Australian Universities (Queensland University of Technology, University of Western Australia, and Curtin University) to explore the key factors using Bayesian Network (BN) analysis, a complex systems approach. The BN model was quantified using coded survey variables and was further compared to write-in responses from a survey of 228 students and 69 supervisors, to explore the benefits of using mixed method analysis in the study of complex phenomena. Key findings indicate that qualitative responses broadly supported the results of the BN analysis, with *supervisor experience*, *style* and *training* identified as key factors. Sensitivity analyses demonstrated that '*student prior experience*' showed the greatest positive influence, whilst '*student obligations*' and '*student attributes*' had the most negative impact on '*HDR student study completion*'. Overall maintaining '*student motivation*' was seen as the single most influential factor on '*HDR student study completion*'. '*CALD student study completion*' can be largely improved through '*supervisor's involvement*' in helping to develop communication and networking skills. Moreover, supervision activities developed through participation of supervisors in respective training programs, followed by improving '*University Support*', made the biggest positive impact on '*supervisor attributes*'. These findings are useful for universities seeking to prioritise areas of funding, whilst also enhancing the performance of CALD students in these disciplines.

Keywords: international students; Bayesian networks; higher degree research; culturally and linguistically diverse students; engineering

1. Introduction

In the modern world of globalisation and international mobility, efforts to attract and retain international students must involve management of issues around 'adaptation to the new country, new cultural practices and expectations'—factors critical to student survival [1]. The global mobility of students reached almost 5 million in 2014, doubling from 2.1 million in 2000, with an annual increase rate of 10%. It is expected to increase by 8 million students annually until 2025, according to projections by the Organisation for Economic Co-operation and Development (OECD). After the USA, UK, Germany and France, Australia is one of the most preferred destinations, attracting half of the world's international students. With the USA and UK's traditional market share declining, Australia and Canada are increasing in popularity alongside intra-regional mobility [2]. Australia, Germany, UK, Malaysia, Germany, and China are rated as the most popular for policies favoring exchange and internationalization [3].

Having contributed 22 billion dollars to the economy in 2016, the education sector in Australia has become the fourth largest export, following iron ore, coal and gold. This is a 10.5% increase from the earnings recorded in financial year of 2015 to 2016 ($19.9 billion), up 17.7 billion dollars on calendar year 2015 ($18.7 billion) [4]. Almost a third (31.7%) of all postgraduate research students enrolled at Australian higher education institutions in 2015 were international students. Of all international student enrolments in Australia, 42.3% were in the higher education sector in 2015, and of those, more than half (53.5%) of international postgraduate research enrolments were undertaking STEM-related courses [5–7].

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In addition to contributing to a global workforce, international higher degree research (HDR) students are a resource for developing and maintaining a diverse, modern, globalised Australian economy. They bring with them knowledge, skills, talent and opportunities for collaborative research, as well as economic and social links that help Australia to sustain high quality human capital and, potentially, maintain competitiveness in the global market [8, 9]. The Bradley Report notes that the greater the number of students pursuing HDR, the greater their potential of making a significant contribution to Australia's skill needs. If Australia seeks to equip itself with the workforce it requires by 2020, it must widen its international student base [9].

The internationalization of teaching and research are critical objectives for most tertiary institutions as they are responsible for raising quality standards and global relevance, attracting the best students and employees, generating revenue, pushing the frontiers of knowledge through research and promoting internal diversity. Research has shown that cultural, linguistic and/or academic differences between students' home cultures and/or institutions and the Australian context, may impact student and supervisor roles and responsibilities, discipline-specific skills expectations, or research approach and requirements for different types of research degrees. Culture is a filter through which we perceive and experience the world. Thus, cultural differences and linguistic diversity may affect a student's communication with their supervisory team, and other students within or beyond the university, in the greater community [10–12]. The complex relationship and interaction between supervisors and HDR students (e.g., PhD, Professional Doctorates or Master by Research graduate students) during the candidature and their role in the successful completion of the degree is well known and recognised [13–15]. However, there is a need to study the diverse influential factors which may impact a student's ability to complete their degree under circumstances of cross-cultural supervision within the Engineering and Information Technology (IT) discipline.

Many studies have examined factors influencing successful completion of HDR degree study [16, 17] and suggested number of predictive indices for timely completion [18]. Due to the complex, multi-faceted and intertwined nature of these factors [19], Bayesian network (BN) modelling has been used in a number of education context [20, 21] to explore the complex relationships embodied in the supervisory relationship. A BN provides a graphical representation for reasoning under uncertainty, where each node represents variables which are either discrete or continuous, and lines with directed arrows represent the connections between each node. The BN is quantified probabilistically through a set of conditional probabilities associated with each node. A BN statistically measures the strength between the variables allowing for probabilistic beliefs to be automatically updated [22], providing a more objective model testing paradigm. Arroyo and Woolf (2005) demonstrated the accuracy of a BN to infer a student's hidden attitude towards learning, content learned, and their perception of the system [23].

This study uses two pre-tested methods to analyse the complex data. Firstly, this paper uses a complex system approach via a BN to model the effect and extent of factors that are perceived by supervisors to influence the degree completion of culturally and linguistically diverse (CALD) students in HDR degrees in Engineering and IT disciplines at three higher education institutions in Australia (Queensland University of Technology [A]; University of Western Australia [B] and Curtin University [C]). Identifying the interaction of individual factors (e.g., personality, learner style, motivation, etc.) and more general cultural and/or academic factors (e.g., educational background, role expectations, understanding of research paradigm, etc.) will provide a sound basis to develop support materials and networks for both students and supervisors. Secondly, these results are compared to qualitative analysis of a write-in responses survey to explore the degree to which these two types of analysis agree.

The Bayesian Network is shown to improve on purely correlational analyses by including directed probabilistic relationships. These directed relationships can also be reversed through Bayes rule, allowing for evaluation of possible configurations of factors that would lead to a stipulated outcome. Moreover, the BN approach offers more opportunities for evaluating and testing these relationships in the context of other influential factors in the outcome. This approach is therefore appropriate for a study to investigate the factors that may influence supervisor perceptions of successful HDR students and student perceptions of supervisors in Engineering and IT.

2. Methods

2.1 Data collection

To fulfil the aims, a mixed method, 5-fold approach was undertaken. The five phases consisted of focus groups, student survey, supervisor survey, a comparison of support services across the three participating universities and critical incident interviews with HDR supervisors of the three Australian universities. Data collected from initial workshops and focus groups, conducted at all three universities, were used to prepare the online questionnaire surveys for this study [24].

2.2 Demography of student/survey respondents

Student data was collected using an online survey, which was administered to 228 HDR students in the areas of engineering and IT at universities A, B and C. The student survey was divided into seven sections. The first section was designed to collect demographic information, including age, gender, country of birth, length of residency in Australia, course information, previous experience at an Australian university, level of previous education, and mode of current enrolment (e.g., part-time or full-time). Other sections were designed to collect the information about students' satisfaction related to supervisors' expertise in the area, interest shown in the students, availability and guidance in the early stages of the postgraduates' candidature etc. Survey data also explored the perceptions of international graduate students in terms of their research environment(s), level of social interaction that students had with their supervisors, as well as their perceptions of their supervisor's enthusiasm to improve their communication and networking skills and discuss non-academic (e.g., personal) issues. There was also an open-ended optional question, which allowed participants to write any further comment on the role of HDR supervision.

2.3 Demography of supervisors/survey respondents

Supervisors' data was collected using online key survey, which was completed by 69 supervisors in the areas of Engineering and IT at universities A, B and C. The supervisor survey was divided into six sections. The first section was designed to collect demographic information and educational background which typically included gender, country of birth, length of residency in Australia, known languages, educational background, experience at international and an Australian university, employment history, field of expertise, and number of HDRs (CALD and non-CALD) students supervised and completed.

The second part of the survey was related to supervisory style and included a series of items related to supervisory satisfaction using a Likert scale (1—Never, 2—Sometimes, 3—Most times, 4—Frequently, 5—Always). These items were related to the obligations of the HDR supervisor/supervisory team and the obligations of the students, the types of activities or responsibilities related to supervision, factors influencing their style of supervision, perceptions of student perceptions of their style, perceptions of behaviours and attributes of successful HDR students, and any factors which may influence completion of CALD and non-CALD HDR student's degree.

The third section explored supervisor perceptions of research supervision in the multicultural context, including a series of items related to supervision of HDR students, especially any perceived differences between CALD and non-CALD HDR students. Using a 5-point Likert scale, participants were asked to rate how relevant cultural, linguistic and/or social factors influenced their supervisory role and whether supervision of CALD HDR student had an impact on the supervisors' research.

The fourth section focused on support structures for HDR supervision. It included items related to availability of HDR support within the individual institution and their use by an individual supervisor. The fifth section explored supervisor perceptions of benefits of supervising within a multicultural context. Finally, the sixth section provided an opportunity for participants to write in comments related to research in the local and global context in more detail using open-ended, optional question.

2.4 Data analysis

The survey data from both student and supervisor surveys was analysed in a number of ways, including descriptive statistics, principal component analysis (PCA), linear regression, and BN Analysis. PCA is a method for merging a set of variables into a combined score (also often called an index). As discussed earlier, a BN graphically represents and then quantifies the relationship between an outcome of interest and the (possibly many, interacting) variables that influence this outcome. It is a common method for modeling complex systems for attitudinal surveys.

2.5 Bayesian network analysis: student survey

The BN was constructed in three main stages: *model creation, model quantification* and then *model interrogation*, based on the student and supervisor survey questionnaire to identify factors which may influence the HDR supervisors in the supervision of CALD/international students in Engineering and IT disciplines.

2.5.1 Model creation

Student Survey: The student survey questions were used to construct the model, with individual questions in the survey forming the 51 outer nodes of the BN. These outer nodes were linked to 9 nodes representing the survey components: student IELTS score, student demographics, student preparation for course, involvement in research program, understand research environment, supervisor involvement, social interaction with supervisor, supervisor obligations and student obligations.

These 9 nodes were, in turn, linked to 3 primary nodes: personal profile, supervisor attributes and student obligations. The 3 primary nodes were linked to an overall outcome node—overall student perception of supervision (OSPS).

Supervisor survey: The supervisor survey questions were categorised into four main nodes: (a) supervisor demographics, which covered areas of personal background (i.e. cultural background, gender, country of birth and area of research) and personal experience in Australia (i.e. length of residency in Australia and previous study in Australia); (b) supervisor perception of a successful CALD student; (c) supervisor perception of a successful HDR student; and (d) supervisor perception of supervisor attributes, which covered areas of supervisor obligations, supervisory style, influence on supervision, support on supervision, participation in training and experience.

2.5.2 Model quantification

For each of the outer nodes, the proportion of respondents that answered 4 or 5 on Likert scale was taken to estimate the probability of 'High'. The probabilities for the inner nodes were estimated using a PCA, which is a means of weighting each question (or node) based upon the variation shown in the responses to a given question along the 5-point Likert scale.

2.5.3 Model interrogation

The probability of a given variable was adjusted to observe its effect on connecting variables. The maximum likelihood scenario with respect to a given factor can be stated in terms of the likelihood or probability of the factor being 'High', represented by the H value, or being 'Low', indicated by the L value. A sensitivity analysis was conducted to assess the relative influence of the factors in the model on the probability of the model outcome. This was run by specifying extreme conditional probabilities (L = 1.0 or H = 1.0) for each node in the network and recording the effect on the target node.

2.6 Linear regression

Linear regression was used to examine the relationship between the students' personal attributes and their attitudes to supervision (student survey), and supervisors' personal attributes and their attitudes to supervision and student success (supervisor survey). The attitudes were considered as the response and the personal attributes were fitted as possible predictors of the response. The aim was to identify personal attributes that significantly impacted on the students' attitudes to the supervisor.

2.7 Write-in responses

Write-in responses from the survey were compiled with Key survey, categorized, and compared to the results of the BN analysis, in terms of degree of support and congruence with the identified nodes and overall analysis [25].

3. Results

The BN model was quantified using coded survey variables and findings were compared to write-in responses to explore the extent to which more 'qualitative' responses were representative on these issues. Key findings indicated that the write-in responses broadly supported the results of the BN analysis. Statistical analysis provided a more generalisable result, whereas the individual observations allowed individual voices to clarify key details, personalising the very human situation of the supervisory relationship.

3.1 Student survey: general analysis

Approximate 71% of participants were studying in the broad area of engineering, including chemical (3%), civil (14%), design (2%), electrical (6%), mechanical (14%), and other or unspecified (32%). Others were studying in areas such as IT (19%), bio-engineering (4%) and other (6%). Most of the respondents (over 70%) were supervised by a team of supervisors, while the rest were supervised by a single supervisor. Other details with respect to participant's nationality, age, gender, qualification length of residency IELTS etc. are presented in Table 1.

3.2 Supervisor survey: general analysis

In total, 60% of supervisors were from University A, 22% from University B, and 18% from University C. The majority were male (81%), with almost half of the supervisors having 'Australian nationality' (48%), followed by the next largest group of nationalities including China, UK, Germany, the USA and Sri Lanka. Other participants were from India, Hong Kong, Italy, Mauritius, New Zealand, PNG, Poland, Serbia, Switzerland, Turkey, Bangladesh and the Czech Republic (Fig. 1). Other details with respect to supervisor's professional, educational and work experience, length of residency and language are presented in Table 2.

3.3 Bayesian network analysis: student survey

The *overall student perception of supervisors* (OSPS) was high (H 80%), indicating that the students had a high level of satisfaction with their supervisors and the supervisory process. Out of three primary nodes, *student obligations* (H 91%) and *supervisor attributes* (H 85%) were the most influential factors on OSPS. However, the effect of *student profile* (demographics, research field, and type of course) was minimal (H 56%) (Fig. 2).

Table 1. General analysis of Student Survey

<table>
<tr><th>Participant's Country</th><th>Percentage</th><th>Age (Years)</th><th>Percentage</th><th colspan="2">Gender Proportion</th></tr>
<tr><td>China</td><td>25%</td><td>20–29</td><td>53%</td><td>Male</td><td>Female</td></tr>
<tr><td>Malaysia</td><td>10%</td><td>30–39</td><td>38%</td><td>67.4%</td><td>32.6%</td></tr>
<tr><td>Iran</td><td>9%</td><td>over 40 years</td><td>9%</td><td></td><td></td></tr>
<tr><td>Sri Lanka, India & Indonesia</td><td>8% each</td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="2" rowspan="2">Enrollment in Higher Research (Full time)</td><td colspan="2">Status of International Study</td><td colspan="2">Length of Residency</td></tr>
<tr><td>previously studied in an Australian university</td><td>25%</td><td>for a year or less</td><td>15%</td></tr>
<tr><td>enrolled in full time PhD research</td><td>82%</td><td>studying first time in Australia</td><td>75%</td><td>spent between 1 to 2 years</td><td>46%</td></tr>
<tr><td>enrolled in Master by Research</td><td>13.2%</td><td colspan="2" rowspan="2">International English Language Testing System (IELTS) Entry Scores</td><td rowspan="2">between 3 to 5 years</td><td rowspan="2">28%</td></tr>
<tr><td>Others (Part time in Ph.D./ Master by research)</td><td>4.8%</td></tr>
<tr><td colspan="2">Highest Level of Qualification</td><td>score 7 or higher in reading</td><td>74%</td><td>between 6 to 10 years</td><td>8%</td></tr>
<tr><td>Master's degree</td><td>67%</td><td>score 7 or higher in listening</td><td>70%</td><td rowspan="3">more than 10 years</td><td rowspan="3">3%</td></tr>
<tr><td>Bachelor's degree</td><td>31%</td><td>score 7 or higher in speaking</td><td>56%</td></tr>
<tr><td>other qualifications like Ph.D. and Graduate diplomas</td><td>2%</td><td>score 7 or higher in writing</td><td>51%</td></tr>
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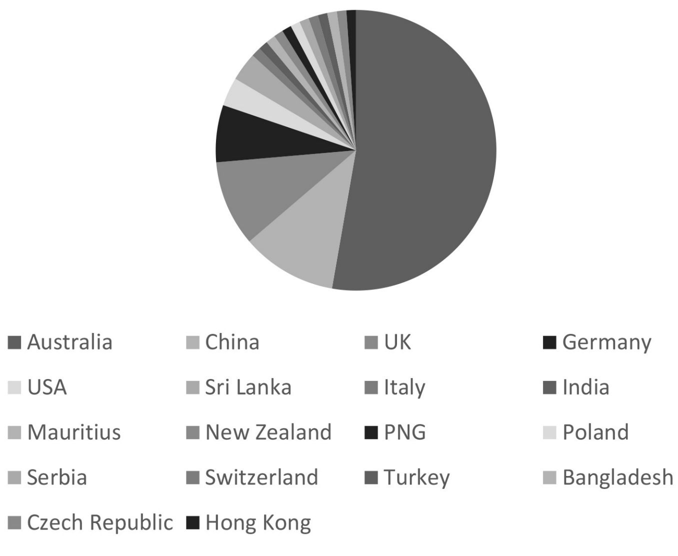

Fig. 1. Country of supervisor's nationality.

Student obligations were more related with adequate planning for submission dates (H 94%), progress meetings with supervisor (H 93%), students' willingness to explore better research methodologies (H 91%), compliance with university reporting procedures (H 90%) and the responsibilities as HDR students (H 90%). *Supervisor's involvement* in the research project (H 91%) and *supervisor obligations* (H 88%) were the two most influential factors for *supervisor attributes*. However, students rated supervisors' availability to discuss research progress (95%) as the top priority under the *supervisor obligations*, closely followed by feedback on written submissions (H 94%).

Overall *supervisors' engagement* in social interaction (H 76%) was lower by 12% as compared to their commitment to research related activities and academic responsibilities. Students felt that the super-

Table 2. General Analysis of Supervisor Survey

Personal, Educational and Work Experience		**Years of Experience (60% are working in the current Universities since last 6 years)**		**Main fields of Supervision and/or Research**		**Language**	
themselves studied in Australian universities	73%	Level E (Professor)	27%	Built Environment (all areas)	12%	English as first language	61%
have work experience in other countries too	70%	Level D (Associate Professor)	24%	Engineering (all areas)	44%		
Length of Residency		Level C (Senior Lecturer)	24%	Mechanical Engineering	14%	monolingual	42%
More 10 years as permanent residents	52%	Level B (Lecturer)	24%	IT (all areas)	18%	Bilingual	37%
1 to 5 years	28%	Level A	1%	Others	12%	Multilingual (3–5 languages)	21%
6 to 10 years	20%						

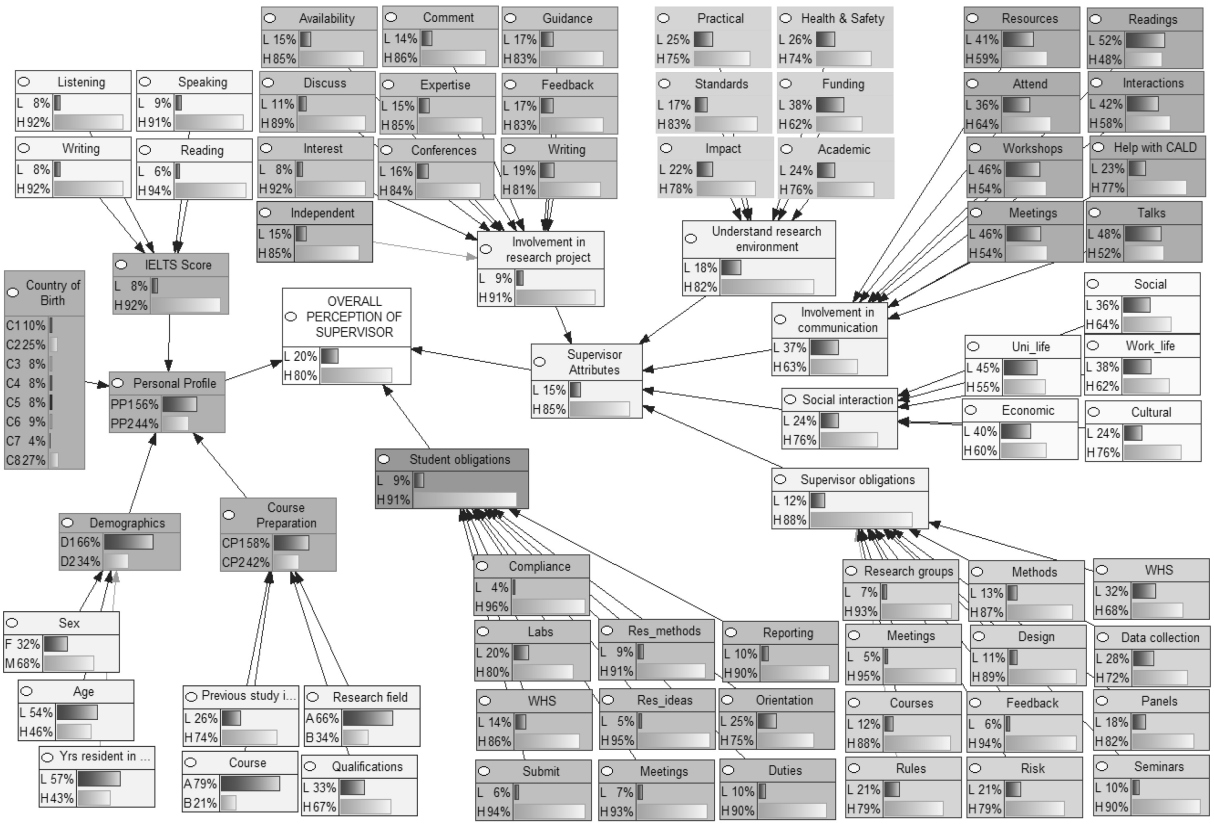

Fig. 2. Complex Systems Model for Student Survey—Quantified Bayesian Network.

visors are considerate about their cultural and religious background, but they are least concerned about their work life balance (H 62%), social needs (H 64%), economic needs (H 60%) and support in educating about university life (H 55%). Supervisors seemed to be considerate for their non-English speaking background (H 77%). However, they were not found to be involved in helping students to enhance their networking and communication skills (H 63%). Supervisor efforts to direct the students to resources (H 59%), relevant workshops (H 54%), encouragement to read (H 48%) or network with other English-speaking (presumably local Australian) HDR students (H 58%), were also low in comparison to other factors.

3.3.1 Sensitivity analysis

The sensitivity analysis of the BN showed that *supervisor attributes* was the most important predictor of *student perceptions* contributing to a 46% difference, followed by *student obligations* with 32% change and *personal profile* with 10% change only in OSPS (Fig. 3).

Supervisor attributes was also the most critical factor that, if allowed to decline, could adversely affect the *overall perception of students* by the great-

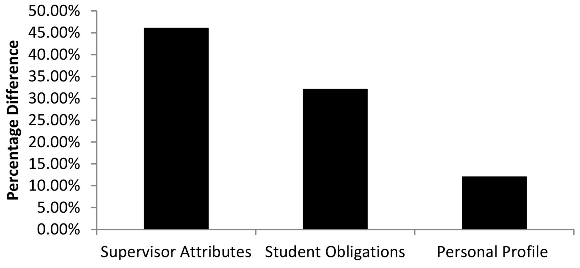

Fig. 3. Sensitivity of Overall Supervisor Perception by parent node.

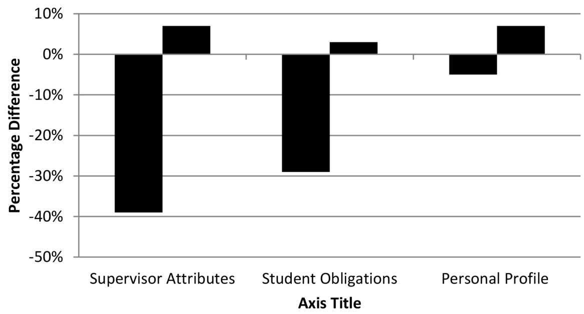

Fig. 4. Change in overall Student Perception from maximum likelihood.

est margin, 39%, while the maximum gain was 7%, followed by *Student obligations* with detrimental effect of up to 29%. The *Personal profile of students* could improve the perception of supervisors by up to 7%, but this is not considered to be a likely scenario in the current context of diversity of student populations (Fig. 4).

The sub node, s*tudent perception of involvement*, in the research project (H 72%), in the BN analysis of supervisors, also showed the highest probability of being positive towards *supervisor attributes*. Student involvement and individual differences were also cited in the write-in comments, with one supervisor noting '*involvement of supervisors depends on the students' character, personality* and *learning style. A balance suitable to all must be reached for effective results*' (Fig. 5).

3.4 Bayesian network analysis: supervisor survey

The BN consisted of 4 primary parent nodes contributing to a single outcome node named *overall supervisor perception of CALD student success* (OSP). Each parental node represented a sub network of categories pertaining to either student or supervisor related aspects (Fig. 5). The BN identified a number of interesting results.

The OSP of H = 44% meant that the probability of CALD student success being high was 44% for

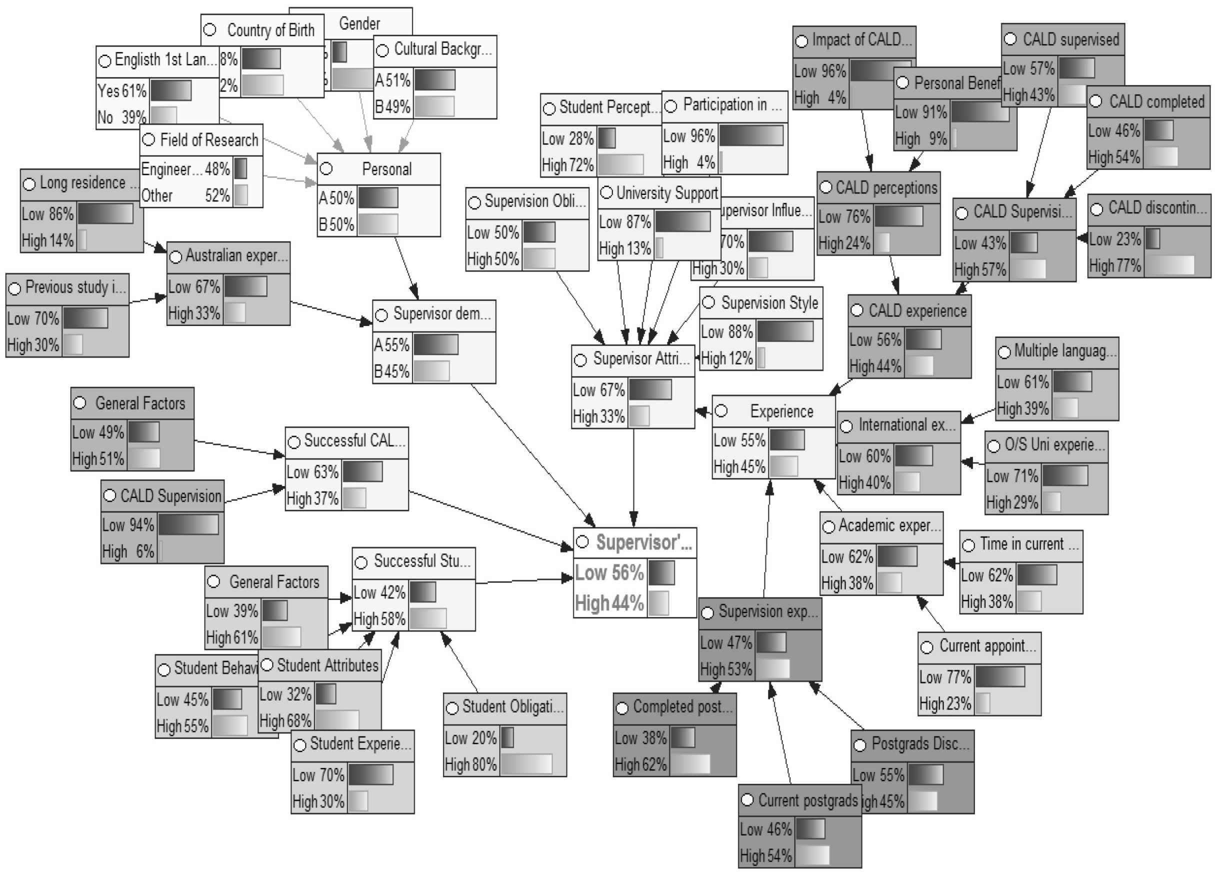

Fig. 5. Complex Systems Model for Supervisor Survey—Quantified Bayesian Network.

the set of conditions investigated. The 4 parent nodes contributing to this overall perception indicated the following probabilities: *supervisor perception of a successful HDR student* (H 58%), *supervisor perception of a successful CALD student* (H 37%), *supervisor demographics* (A = 55%, B = 45%) and *supervisor attributes* (H 33%). The distinction between *supervisor demographic A* and *B* is best understood when related back to the parent nodes associated with categories *personal attributes* and *Australian experience* and cannot be simply identified as a set of individual characteristics.

The node *successful HDR student* (H 58%) had a greater probability of being high when compared to *successful CALD student* (H 48%). The contribution that *supervisor attributes* made towards student success only had a 33% chance of being high. Overall, this finding suggests that qualities among students to complete the HDR degree contributed more, compared with CALD supervision-related factors or *supervisor attributes* alone for *overall perception of CALD success*. This was also reflected in the perspective of many supervisors—qualities like timely completion and English proficiency, in terms of good communication, make for successful HDR students, irrespective of whether they were CALD or non-CALD. The analyses also indicated that the sub node *student perception of involvement* in the research project (H 72%), *supervisor experience* (45%) and *supervisory style* (H 30%) showed the highest probability of being positive towards *supervisor attributes*. A positive response for overseas university experience (p = 0.056) and a longer time in the current appointment (p = 0.035) were each associated with a significantly higher score in regression analysis.

These results are supported by write-in comments, where a number of supervisors explicitly stated that they do not differentiate CALD and non-CALD students in terms of possessing 'successful HDR characteristics'. One of the supervisors stated:

> "I find the differences are more between full-time and part-time HDRs than the cultural/language diversity".

Another stated:

> "I do not see differences in these areas between different groups of students".

Yet another explained that:

> "Every student (CALD or non-CALD) is unique, they all have their individual issues like health problems, family stress, etc. I think a supervisor should be sensitive to understand their issues and offer more-or-less assistance as per their need. This approach will help in addressing particular issues of CALD students and find a mutually acceptable way to accommodate them".

3.4.1 Sensitivity analysis

The overall perception of a *successful CALD student* was most sensitive to changes in *supervisor demographic B* (24%), while each of the other three categories indicated a 22% change (Fig. 6). Of those, *supervisor attributes* can be improved by 15% and *successful CALD student* by 14%. A decline in the roles and responsibilities of a *successful HDR student* can lead to a decline of 13% in the overall perception of CALD completion, followed by 12% decline for changes in *supervisor demographic B* (Fig. 7).

A sensitivity analysis of the *supervisor attributes* sub-network suggests that *participation in supervisor training, supervisor style* and *university support* are equally important factors for predicting perceptions of *supervisor attributes*, collectively contributing 14% difference in each node (Fig. 8). Student perceptions of their supervisors' involvement in research were the next most important factor in this analysis and contributed 13% difference in *supervisor attributes* and *supervisor influences* along with experience and *supervisor obligations* (Fig. 9). The full results of the sensitivity analysis are depicted in Table 3.

The node, *supervisor obligations*, had little influence on *supervisor attributes* (H 50%). This study found that *supervisor participation in workshops*

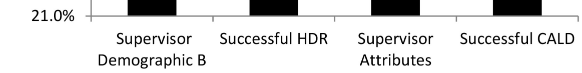

Fig. 6. Sensitivity of overall perception of CALD student success to changes in parent nodes.

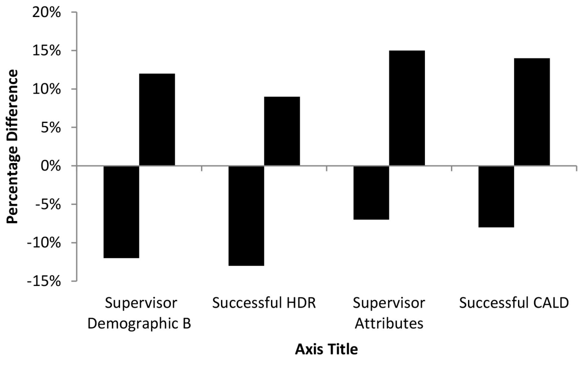

Fig. 7. Change in CALD-HDR completion from Maximum Likelihood scenario by parent node.

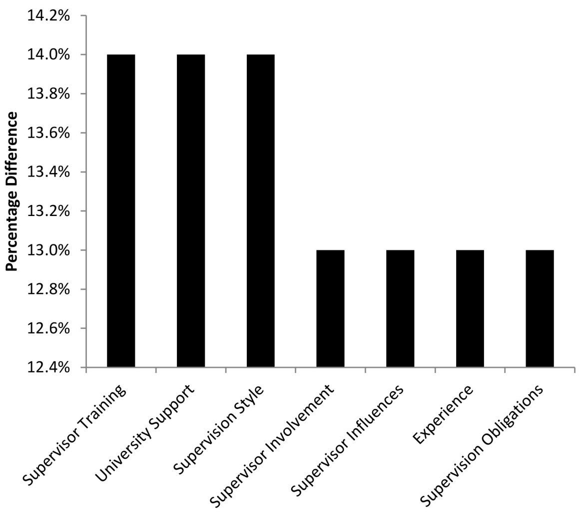

Fig. 8. Sensitivity of supervisor attributes to changes in parent nodes.

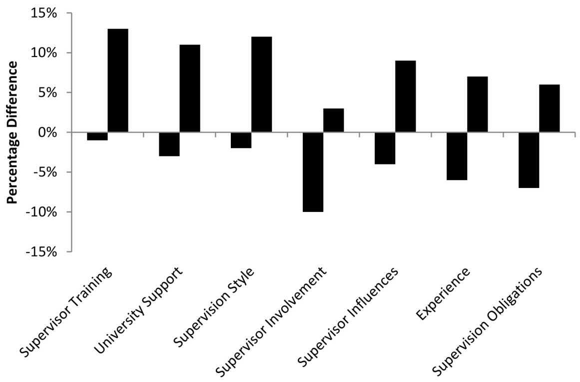

Fig. 9. Change in supervisor attributes from Maximum Likelihood scenario by parent node.

appeared to contribute little towards *supervisor development* and *competency* (H 4%). However, findings indicated that 81% agreed their supervisory style has been influenced by how they supervised HDR student; discussions with senior and more experienced colleagues (73%); and refinement based on their personal reflections on their supervisory experiences (90%). Interestingly, 61% agreed that their supervisory style was influenced by cultural factors on communication style (e.g., formality, deference for authority, status). The same results were found by other researchers [25] and the participants' write-in comments.

> "Areas of challenge in supervision: getting CALD students to think critically; allowing students to be more independent; in many areas, the HDR should organise and lead, and not expect the supervisor to do it. Other obligations: However, this needs to be explained to those CALD students who may not culturally be comfortable with this. In most cases the self-starters produce better results'; try to continue practising the good qualities that you had before you left your home country."

The node *supervision style*, which was defined by the degree to which supervisors engaged in different supervision-related activities, contributed less towards *supervisor attributes* (H 12%). The regression analysis results indicated that the *length of residency in Australia* was positively correlated with participants' responses regarding *supervision style* and were almost significant at the 5% level ($p = 0.052$). This result suggests that *supervision style* appears to be influenced by *length of stay in Australia*, with experience of the Australian academic system having a positive influence on supervision of students within that system.

The other variable associated with responses on *supervision style* was whether the supervisor worked with *CALD students who have discontinued* ($p = 0.015$). A positive response to this question was associated with lower scores regarding *supervision style*, meaning the discontinuation of a CALD student may have been related to the lower level of

Table 3. Sensitivity of supervisor attributes to changes in parent nodes

Parent Node		**Probability of Supervisor Attributes being High**	**Difference from ML**	**Difference**
Supervisor Training	Low	32%	–1%	14%
	High	46%	13%	
University Support	Low	30%	–3%	14%
	High	44%	11%	
Supervisor Style	Low	31%	–2%	14%
	High	45%	12%	
Supervisor Involvement	Low	23%	-10%	13%
	High	36%	3%	
Supervisor Influences	Low	29%	–4%	13%
	High	42%	9%	
Experience	Low	27%	–6%	13%
	High	40%	7%	
Supervisor Obligations	Low	26%	–7%	13%
	High	39%	6%	

engagement by the supervisor on supervision-related activities. This may be hypothetical due to the small sample size. In fact, the majority of supervisors (72%) were not supervising many CALD students (numbers were 0–2), out of which 45% had never experienced any discontinuation.

Regression analysis indicates that higher scores on *supervisor participation* were associated with *increased time in current appointment* (p = 0.029). Scores for this component were also substantially affected by the nodes *field of research* (p = 0.081) and *currently supervising (many) postgraduates* (a positive response led to a lower score, p = 0.068). These results suggest that opportunities for participating in workshops increase with duration on the job, so the correlation may be spurious. S*upervisor confidence of support* given by university or faculty was low (H 13%). Increased support offerings at the university level may provide supervisors with greater opportunity to access training. For example, one supervisor complained as follows:

> "Too little support is provided by the university HDR administration. For example, why can't I obtain culturally appropriate protocol advice?"

3.5 HDR versus CALD students success

3.5.1 General HDR completion

A successful HDR student was a general category, which included all HDR students including CALD and non-CALD students. *Supervisor perception of student obligations* was high (H 80%), followed by *student attributes* (H 68%), *general factors* (H 61%) and *student behaviour* (H 55%). *Previous student experience* was perceived to be least important (H 30%).

Regression analysis results indicated that *student behaviour* (H 55%) was significantly associated with gender (higher score by female supervisors, p = 0.023), *residency of supervisor in Australia* (longer residency associated with higher scores, p = 0.038) and *overseas university experience by supervisors* (positive response associated with higher scores, p = 0.003). *Previous study in Australia* by supervisors was near statistically significant (positive response associated with lower scores, p = 0.067). These results indicate that supervisors' experience with CALD students, and experience within the Australian academic system and in cross-cultural contexts, have a strong positive effect on HDR completions. As does gender of supervisors. It was found that female supervisors were more involved in the pastoral care issues, which were identified previously as important factors in CALD HDR student perceptions.

Similarly, *student attributes* were significantly associated with *supervisors' overseas university experience* (positive response associated with higher scores, 0.027) and with *currently supervising many postgraduates* (positive response on this variable was associated with lower scores on student attributes, p = 0.015). *English as first language* (positive response associated with higher scores, p = 0.078), *current appointment* (positive response associated with higher scores, 0.063), and *supervisor has had CALD students who have discontinued* (positive response associated with lower scores, p = 0.067), were all associated with *student attributes* at the 10% significance level. This emphasises the important point that supervisors' long-term association with the Australian culture helps them to identify successful student attributes. *Long residency time in Australia* (p = 0.056), and *overseas university experience* (p = 0.057), two variables with strong, but not statistically significant results, were also associated with *student obligations*. The positive response to *previous study in Australia* was associated with a lower score for student experience (p = 0.035), while positive response to *overseas university experience* was associated with a higher score for this component (p = 0.012). These two associations may indicate different research cultures between Australia and some other parts of the world. Further research is necessary to clarify these differences.

3.5.2 CALD specific success

The category *successful CALD student* (H = 37%) was influenced by *general factors* (H 51%) and *CALD supervision* (H 6%). CALD supervision related to three areas: supervisor's previous experience with CALD students; supervisor awareness of what was important for completion of CALD students study; and supervisor input. It showed that the overall influence of supervisors on CALD-specific supervision was very low (H 6%). Many supervisors saw their association with CALD students as having a significant positive impact on them (p = 0.021), and others noted that having CALD students supported their own research (p = 0.058). One of the supervisors commented that having CALD HDR students

> "helps to make (their) international networking".

Another noted,

> "the HDR postgraduate students I have supervised were overwhelmingly CALD students. Thus, I cannot make any meaningful comparison. For me the whole matter is a non-issue".

However, many academic issues such as genre-specific and/or discipline-specific writing and speaking skills, and overall project issues, were also identified as CALD specific.

For example, some comments include:

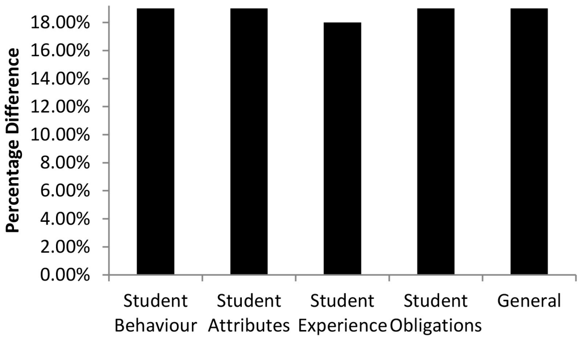

Fig. 10. Sensitivity of successful HDR by parent node.

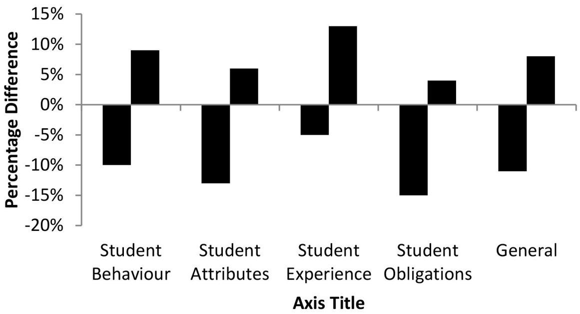

Fig. 11. Changes in successful HDR from maximum likelihood.

"Students for whom English is a second language generally tend to need more help with their writing and presentation skills".

"The key difference between HDR students, regardless of cultural background, is the ability to write in clear scientific English".

"It is true that I am less demanding of international students and help them to write (rewrite) effectively".

"HDR projects should be designed to the student, and this is especially the case for CALDs. This needs to be considered by the supervisors".

3.5.3 Sensitivity analysis

The sensitivity analysis of HDR completion shows that all categories are equally sensitive (17%), except for *student experience* which is 16% (Fig. 10). Improving on the *student experience* placed the highest impact on overall HDR study completion at 12%, followed by *student behaviour* at 9% and *general factors* at 8% (Fig. 11). On the other hand, a lower score on *student obligations* can negatively influence the HDR student study completion by 15%, or by 13% for a decline in *student attributes. General factors* and *student behaviour* are also sensitive to losses of up to 10% (Fig. 11).

4. Discussion

The finding of a 44% chance of a high OSP value, obtained from the BN network model in this study, indicates that there is room to improve understanding of the factors related to CALD student success. The results suggest that *supervisors' perceptions* of the characteristics of a successful CALD HDR student are primarily influenced by their perceptions of the characteristics of successful HDR students (in general), rather than factors that are specific to CALD supervision.

The current results can be categorised into following sub sections:

4.1 Perceptions of student and supervisor roles

Overall, the students appear satisfied with the core supervisory issues related to their research programs, including their supervisors' level of expertise in specified research area, and the amount of interest shown in the students' work. Confusion appears to exist, however, regarding student and supervisor responsibilities to keep the student informed on programs and administrative issues. These differences in role perceptions as key factors appear to be supported by survey results show that, while students felt that their supervisors were generally considerate of their linguistic and cultural backgrounds, they felt their supervisors were less involved in helping students to access language skill development resources or providing support for non-academic and/or personal issues.

4.2 CALD student's success related factors

The results of this study identify CALD *student obligations* as the highest contributing factor influencing their perception of their supervisors. The higher the level of responsibility students felt towards their obligations, the higher the overall expectations they placed on their supervisors' role in helping them to achieve academic success.

Motivation and a positive mind set are key attributes for student success [24]. Factors negatively influencing motivation can have far reaching consequences in the overall performance of the students. Lack of motivation and consequently ignoring all student obligations causes the probability of HDR study completion to decline by a total of 28%, indicating that the combined effect of these two nodes is greater than the sum of the individual effects.

Motivation from the supervisor, help in conceptualisation of the research topic and establishing context for the research, both within the university and in the global context, and timely written feedback on their research, were found to be crucial and significant factors to ensure the overall success of HDR students. Most of the CALD students expressed that they are already intrinsically motivated, based on their ownership of obligations and ambition for a research career at a higher degree level, which generally demonstrates their willingness to pursue knowledge and achieve academic success. The role of supervisor, however, becomes crucial to help them in maintaining the balance between intrinsic and extrinsic factors and meeting their expectations through a variety of roles in guiding them towards academic success. Students valued the availability of their supervisor to meet them at their point of need, ahead of their technical expertise. The expectation of support and time from supervisors were high at the initial stages of their research. This was also noted in prior literature which outlined that the aim of the supervisor was to gradually adapt their supervisory role from being a nurturer at the initial stages requiring substantial time, to collaborator providing assistance in the experimental stages, to facilitator offering feedback in the write up stages, thus progressively reducing the time commitment at each stage of the supervisory process [26]. Strategies to involve supervisors may improve CALD student interaction, socially & academically. Supervisor's involvement is particularly valued by CALD students and a decrease in supervisor's involvement can delay the result between first and second stages of the supervision process due to difference in student and supervisor expectations [24].

The BN analysis also indicated that OSP was positively influenced by the node CALD student success. The model predicted a change from 48% to 65% chance of CALD student success by improving supervisor involvement in communication and networking. The 'availability' of the supervisors is not limited to an academic role as far as the CALD students are concerned. Their need for social interaction with their supervisor had the same level of influence on student perception as their involvement to help them in understanding the research environment. The cultural background of the student further complicates student expectation as seen by the different responses that *student country of birth* elicited for social interaction. Some cultures are far more relational and would expect to establish a trusting relationship before establishing the business relationship between the supervisor and the student (e.g., Middle Eastern), while in other cultures (e.g., Western), business is of foremost importance and socialising takes place after the business relationship has been established. It is therefore important for supervisors to establish the expectations of students within their cultural context at the outset of the project so that expectations on both sides may be evenly met. Effective communication channels between supervisors and students from CALD backgrounds should be encouraged to increase interaction at an academic and social level as one of the effective factors in timely completion of HDR degree.

Managing supervisor's involvement is an equally important strategy for enhancing *supervisor attributes* followed by *supervision obligations*. These results suggest that success in supervision of CALD HDR students may be influenced strongly by personal experience, especially experience with CALD students and/or personal experience living and working in different cultures (e.g., international experience), rather than specific interventions such as *supervisor training*, mentoring or input from senior colleagues or reading literature on supervision practices. These results were consistent with results from the larger survey, as well as comments from participants who indicated that they 'learnt to supervise by how they were supervised' (e.g., an implicit apprenticeship model), rather than professional development or research. Similar results were also seen in earlier studies [9].

For example, one supervisor reflects on how their experience with Islamic students have broadened their cross-cultural understanding, making them aware of inconsistencies in the university:

> "Curiously we bring in CALD students (particularly Islamic ones) and in some parts of the university's operation, we take it very seriously, yet other parts of the university's do (not). My favourite example is the swimming pool. Female Islamic students need to swim unobserved by men, but our pools are viewable by any passers-by and we have no women-only sessions; we make no concessions to their needs whatsoever, but if I were to host a student function and serve only bacon sandwiches, there would be a furore (rightly)".

It is interesting that while many supervisors showed their concern and point out 'language' as a key issue with CALD students, data shows that the majority of students had IELTS scores in the range of 6 and 7. Although these scores may be expected based on entrance requirements in most Australian universities, it seems significant that most students had higher scores (7 or higher) in the receptive skills (reading and listening), than in the productive skills (writing and speaking). This result may reflect the importance of productive skills in academic and social interactions in the Australian context and may be an important factor in integration and success. The ability to speak and write effectively in English would theoretically benefit academic productivity and survival in an English-speaking country such as Australia. It is necessary for HDR student to understand the Australian academic context, the specific institutional expectations of their host university, and the expectations of the various members of their supervisory team. These all may become difficult if there is a lack of effective English communication. Lack of ability and confidence to communicate in English may reduce their interaction and limit feedback on their work [14]. Universities are encouraged to find ways to enhance the participation of non-English speaking background students to undertake an English course upon their commencement. Prior research also indicates that university policies through administrative and language support played very important role to promote student-supervisor relationship and academic & social wellbeing of international students [27]. One of the participants stated:

> "My supervisor sometimes thinks that he knows everything about my research. He does not give me a chance to express my ideas and I feel this is due to my English not being so good. I am quite shy too'.

Improving the success of HDR students based on prior experience is not a practical solution for existing students. Although supervisors did not consider having a postgraduate qualification as an important experience for higher degree research, the emphasis on experience in research methods and problem-solving ability implies that postgraduate experience, and/or prior research experience, may be useful. The study suggests that entry requirements in terms of student's problem-solving attitude, foundation knowledge in area of research discipline and research experience should be rigorously considered by academic institutions. Academic institutions should also be proactive in arranging training on understanding of research methodologies [24]. Identifying critical areas for development of targeted interventions (e.g., workshops, tutoring) for specific student cohorts, such as language or cultural support, and/or discipline-specific skills, could be helpful.

While seeking students with more experience in their own disciplines seems to be the best solution towards improving the probability of HDR study completion, universities can equally invest towards developing the relevant skills of existing students. It is also important to maintain programs and other avenues towards helping students continue with their current obligations and create environments to nurture attributes which are deemed beneficial for HDR study completion and ensure sustainability of these practices within the HDR student communities. Australian universities have responded to this by putting in place a range of supervisory frameworks to help international students settle more easily into the different research cultures. Efforts to improve research training performance have emphasized the importance of timely, and high-quality research degree completions. Examples of such programs include the 'Research Training Scheme' (RTS), University of Technology Sydney's 'First Consortium', Queensland University of Technology's 'Introduction to Research for International Students' and University of Western Australia's 'Facilitating International Research Students Transition Program'.

4.3 HDR supervisions related factors

According to the sensitivity analysis results on the sub network *supervisor attributes, supervisor participation in training* (13%) and *supervision style* (12%) were the most influential nodes for a positive change in outcome, followed by the node *university support to supervisors* at 11%. The most negative influences on supervisor attribute were from nodes *supervisor involvement* (10%) and *supervisor obligations* (7%). University support can be improved by addressing the issue of supervision time by increasing the weight of HDR supervision in the workload equation and adding extra load for CALD students. Support can also be increased by increasing funding for HDR scholarships and research facilities, and by arranging specific training, workshops & seminars for personal development of the supervisors. Training should be expanded to include cross cultural communication issues, pastoral care emphasis, and coaching towards building motivation among students. Participation in training can be improved by catering to a style that involves personal experience and a personalised approach involving self-reflection. After all, the present study shows that majority of supervisors learn by their own experience and leaning. Improving supervisor support, modifying *supervisor style* (if necessary), and providing relevant *supervisor training* could lead to an overall improvement in *supervisor attributes* up to 37% (from 33% to 70% likelihood) according to the current model.

Some limitations of these conclusions exist, given the restrictions of the method. Specifically, the survey used to quantify the supervisor model was written and completed before the construction of the BN model. The BN model was then derived using PCA based on the supervisors' answers to questions on the survey. This is not the most desirable method of model construction and quantification, as it relies on the survey being constructed from random questions. For example, if the survey was written to measure levels of five constructs, it is likely that the PCA would produce five nodes. This can tell little more compared to the survey alone. Although the model does allow for more interrogative assessment of the results, compared with traditional static analyses, there is little indication of whether unnecessary factors have been included, or necessary factors excluded, by using this method.

There are number of limitations of BN models. The first major limitation of such models is their inability to cope with cyclical phenomena without introducing new elements to the modelling paradigm. Hence, this excludes the modelling of complex system components, such as, feedback loops which lead to emergent behaviours [28]. Another limitation noted by other researchers stems from the discretisation of nodes when modelling any unobservable system [29]. Most applications of BN models (including this one) require nodes to be broken into discrete states to create conditional probability tables. In most cases, nodes are broken into two states, which require that some threshold or cut off be arbitrarily created by the researcher [22]. By doing this, it is difficult to tell whether each expert that quantifies the model has the same definition of the threshold, or that the threshold that has been chosen is most appropriate to modelling the system of interest. An inappropriate choice of threshold could easily lead to a model that is either overly sensitive, or not sensitive at all, to changes in the state of the system. Nevertheless, BN was used in this study as it is superior to both Analysis of Variance (ANOVAs) and the Structural Equation Model (SEM). These are both designed to test specific hypotheses about equality between means and other post-hoc tests required to elucidate the nature of any inferred inequality. Furthermore, ANOVAs and SEMs lack the interactive capability of BN models to undertake scenario assessment (forward inference) or inverse assessment (backward inference). Moreover, this model can reflect, in a straightforward manner, structures that reflect a linear regression and a SEM.

5. Conclusion

Best practices for supporting supervisors and students can be developed around factors identified in this research. The qualitative data has invited several strategies for dealing with these concerns on an individual basis when they arise. Improvement in the model to include a broader definition of HDR study completion in the Australian context may provide greater insight into managing student supervisor interactions and help to improve the overall effectiveness of the HDR experience for both students and supervisors alike. Most of the factors are common to all academic disciplines, to a greater or lesser extent. However, there are certain factors that are specific to engineering and IT disciplines. The data reveals that international/CALD HDR students currently attempt to perform at their best, however, there are existing services that can assist these students for better performance. Present research finds that student and supervisor perceptions are generally positive and there is little difference between international and domestic students. The critical incident interviews reveal that some supervisors face challenges due to cultural and language variations that may make them hesitate to support CALD students.

The management of students in relation to their obligations is important to ensure their ultimate success, and in that regard, the supervisors can play an important role in ensuring that students are both aware of, and comply with, university requirements and protocols. A lapse in student focus and motivation is a particularly significant concern because the key obligations require students to be proactive in organising their own research related activities and actively engaging the supervisors through regular meetings. This analysis suggests that increasing the likelihood of participation in *supervisor training* is the most important strategy for improving support for supervisors working with CALD and international students, followed by high university support, and improving individual *supervisor's style*. Having a formalised milestone preparation requirement could help both supervisors and students remain on track, leading to overall improved completion times.

Future research should look at developing a complete and parsimonious model at the outset, using a validation framework. Once a valid BN structure has been derived from expert opinion, published research and validity test results, the survey can be constructed to allow for quantification of the model. An advantage of this approach is that it produces a clean, easily interpreted, descriptive model which is capable of probabilistic interpretation and simulation of hypothetical scenarios. The extent to which a supervisor's perceptions are influenced by their own cultural background and educational experiences will be analysed in the future research.

Acronyms: HDR: higher degree research; BN: Bayesian Network; CALD: culturally and linguistically diverse; OSPS: overall student perception of supervisors; OPS: overall supervisor perception; PAC: principal component analysis

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