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Comparative Study of Data Analytics Readiness between ISEC and Non-ISEC Faculty

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Abstract

Non-international scholarly exchange curriculum programs follow traditional educational frameworks may not help to refine educational processes. To overcome this shortcoming, this study determines the differences in data analytics readiness between international scholarly exchange curriculum and non-international scholarly exchange curriculum faculty in Chinese higher education institution. By using DELTTA instrument, the findings suggest that (i) expanding diverse samples, investigating multidimensional relationships, and leveraging mixed methods are key future directions, (ii) culturally responsive research will empower diverse faculty by uncovering nuanced insights to guide the development of inclusive big data analytics policies and environments in our increasingly data-driven educational landscape, and (iii) highlighting the need for targeted interventions to ensure uniform big data analytics readiness across diverse academic domains.

Keywords: DELTTA; Big data analytics; Scholarly exchange curriculum; Academic

1. Introduction

In the information age, data analytics has become essential for improving decision-making and operational efficiency, particularly in education. The advancement of big data technologies has transformed higher education, making data analytics a critical skill for faculty. By 2020, over 90% of the world's population had completed basic education, generating massive amounts of educational data (UNESCO, 2018). The number of internet users increased to 5.3 billion by 2023, providing extensive data from online learning platforms. The COVID-19 pandemic further accelerated online education, enhancing the data available for improving educational outcomes (Li et al., 2020).

The International Scholarly Exchange Curriculum (ISEC), affiliated with the China Scholarship Council (CSC) and part of the "China's Education Modernization 2035 Plan," targets local and provincial colleges and universities in China. It aims to foster international exchange and improve competitiveness by integrating international educational resources into the local curriculum, emphasizing professional development through regular training and assessments. In contrast, non-ISEC programs follow traditional educational frameworks without these additional components.

The integration of data analytics in higher education is widely recognized for its capacity to refine educational processes, including curriculum design, student performance evaluation, and institutional governance (Daniel, 2017). Data analytics, involving statistical and computational methodologies to analyze extensive educational datasets, is instrumental in elevating teaching quality and learning outcomes. However, readiness to adopt and effectively utilize data analytics tools varies significantly among faculty members, influenced by demographic and professional factors (Gibson, 2017).

This study investigated the differences in data analytics readiness between ISEC and non-ISEC faculty in Chinese higher education institutions,. The primary research question is: "Is there a statistically significant difference in data analytics readiness between ISEC and non-ISEC faculty?" To address this question, a comprehensive survey was conducted across multiple universities, analyzing the collected data using statistical methods to identify significant patterns and differences.

Employing a non-experimental causal-comparative research design, this study utilizes the DELTTA instrument, based on Davenport's model, to gauge data analytics readiness across six elements: data, enterprise, leadership, targets, technology, and analysts (Davenport et al., 2010). The study's sample comprises 154 faculty members from both ISEC and non-ISEC programs at Chinese universities, selected via snowball sampling. Data were collected through surveys and analyzed using descriptive and inferential statistics, including independent samples t-tests and two-way ANOVA.

Understanding the factors influencing data analytics readiness among faculty is crucial for developing targeted interventions that enhance data literacy and analytical skills. This study provides valuable insights for educational leaders and policymakers in designing effective training and support programs that address the specific needs of different faculty groups. By improving data analytics readiness, higher education institutions can leverage data-driven decision-making to enhance educational quality and institutional effectiveness.

2. Theoretical Framework

Five theoretical frameworks are compared: Data Analysis Value Chain Model (DAVCM), Data Analysis Capability Model (DACM), Data Analysis Maturity Model (DAMM), Data Analysis Lifecycle Model (DALM), and the DELTA Model. DAVCM covers the data analysis lifecycle but oversimplifies complexity (Curry, 2016; Król and Zdonek, 2020). DACM evaluates data analysis capabilities but lacks empirical support (Król and Zdonek, 2020). DAMM outlines data maturity stages but overlooks the dynamic nature of data analysis (Król and Zdonek, 2020). DALM provides comprehensive tools but is complex and abstract (Stodden, 2020).

This study adopted the DELTA model by Davenport et al. (2010), which balances comprehensiveness and manageability, making it suitable for higher education. It includes data, enterprise, leadership, technology, targets, and analysts, ensuring strategic alignment with institutional goals.

Table 1: Comparative analysis of data analysis models

Model	Description	Strengths	Weaknesses
Data Analysis Value Chain Model (DAVCM)	Describes the full lifecycle process of data analysis	Helps understand the purpose, scope, and methods of data analysis	Over-simplifies ignore environmental influences

continued

Data Analysis Capability Model (DACM)	Assesses data analysis capabilities and prerequisites	Provides a comprehensive capability framework and assessment tools	Lacks empirical support, ignores different stages
Data Analysis Maturity Model (DAMM)	Describes maturity stages of data analysis	Provides a clear development path	Overly idealized, ignore dynamism
Data Analysis Lifecycle Model (DALM)	Provides concepts, principles, methods, and tools for data analysis	Helps design and execute data analysis projects	Overly complex and abstract, with low feasibility
DELTTA Model	Evaluates data, enterprise, leadership, targets, analysts	Comprehensive, practical, adaptive, and suitable for higher education	May overlook some analytical details

Note: The table presented above has been compiled by the author based on a synthesis of relevant literature.

3. Methodology

Campbell and Stanley (1963) noted that causal-comparative research is ideal for non-experimental studies that describe disparities between naturally occurring groups without manipulating variables. This design was chosen to examine differences in data analytics readiness between ISEC and non-ISEC faculty, exploring potential causes and associations. It effectively identifies significant differences between groups (Proudfoot et al., 2018). Two research questions guided the study:

RQ1: Is there a statistically significant difference in Big Data Analytics (BDA) readiness between ISEC and non-ISEC faculty?

RQ2: Are there significant differences in BDA readiness elements (data, enterprise, leadership, targets, technology, and analysts) between ISEC and non-ISEC faculty?

The study used the DELTTA model (Davenport et al., 2010) to assess readiness across six elements: data, enterprise, leadership, targets, technology, and analysts. The sample size was estimated using G*Power 3.1.9.7, considering an effect size of 0.5 medium level, a significance level of 0.05, and a power level of 0.80. The analysis required a minimum of 64 participants per group. To ensure robustness, 160 participants (80 ISEC and 80 non-ISEC faculty) were recruited, exceeding the minimum by 25%. Snowball sampling was employed to reach the required sample size (Sadler et al., 2010).

Table 2: The six elements of the big data readiness assessment survey

Element	Element Description	Sample Question
Data	Data is the most fundamental component of a big-data setup and is a vital determinant of the success of a big-data initiative. Data can be obtained from external or internal sources and can be structured or unstructured.	We have access to very large, unstructured, or fast-moving data for analysis.
Enterprise	An enterprise approach to big data is crucial to achieve big data readiness and maturity. It entails unifying a big-data initiative across the entire organization.	We employ a combination of big data and traditional analytics approaches to achieve our organization's goals.
Leadership	Leaders in big-data-ready institutions should be passionate and committed to adopting and implementing the technologies. In addition, they must have a disruptive mindset, meaning that they are ready to disrupt the status quo and try new, risky approaches and are also willing to experiment with data on a large scale.	Our senior executives regularly consider the opportunities that big data and analytics might bring to our business.
Targets	Targets imply that an institution must identify where big-data analytics will be applied within the institution	We prioritize our big data efforts to high-value opportunities to differentiate us from our competitors.
Technology	Technology aids in the management and analysis of data. Big data entails large volumes of structured and unstructured data and the relevant technologies that enable data processing and analysis.	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing.
Analysts	Analysts represent the human side of big data and are crucial to the initiative's success. Adopting and deriving meaningful information from big data requires a literate workforce and data scientists focusing specifically on data operations.	We have a sufficient number of capable data scientists and analytics professionals to achieve our analytical objectives

Note: Adapted from Big data at work: Dispelling the myths, uncovering the opportunities, by Thomas Davenport. Copyright 2014 by Harvard Business Review.

4. Data Analysis

Participants' Demographic Profiles

This section demonstrates participant demographic profiles based on the survey responses from 154 faculties at 10 ISEC member universities in China. Participants voluntarily provided information on name, gender, age, institution, teaching experience, rank, education, discipline, ISEC participation, and faculty type. Most participants were from Inner Mongolia (n = 59, 38.3%), followed by Hebei Province (n = 21, 13.6%), Jiangxi Province (n = 18, 11.7%), Guizhou Province (n = 15, 9.7%), Fujian Province (n = 14, 9.1%), Liaoning

Province (n = 14, 9.1%) and Guangdong Province (n = 13, 8.4%). In terms of gender, there were more males (n = 81, 52.6%) than females (n = 73, 47.7%). For professional ranks, most were lecturers (n=83, 53.9%), followed by associate professors (n = 51, 33.1%), professors (n = 14, 9.1%), and teaching assistants (n = 6, 3.9%). Regarding education background, most held master's degrees (n = 114, 74%), followed by doctoral degrees (n = 33, 21.4%), and bachelor's degrees (n = 7, 4.5%).

Descriptive Statistics of Variables

Descriptive statistics were calculated for the DELTTA readiness scores (see Table 7). The composite score combining all DELTTA subscales was lower for ISEC (M = 3.52, SD = .83) versus non-ISEC faculty (M = 3.71, SD = .83). The minimum score was 1 for ISEC and 1.73 for non-ISEC faculty. Median scores were 3.67 and 3.73 for ISEC and non-ISEC groups respectively. The individual subscales of the BDA adoption readiness mean scores are displayed in Table 8. The mean scores for each of the elements for the ISEC and non-ISEC faculty helped to address RQ2.

Table 3: Overall BDA readiness scores of ISEC and non-ISEC faculty

Overall BDA	n	Range	Minimum	Maximum	Mean	SD
ISEC	77	4	1	5	3.52	.83
Non-ISEC	77	3.27	1.73	5	3.71	.83

Table 4: Individual BDA readiness score of ISEC and non-ISEC faculty

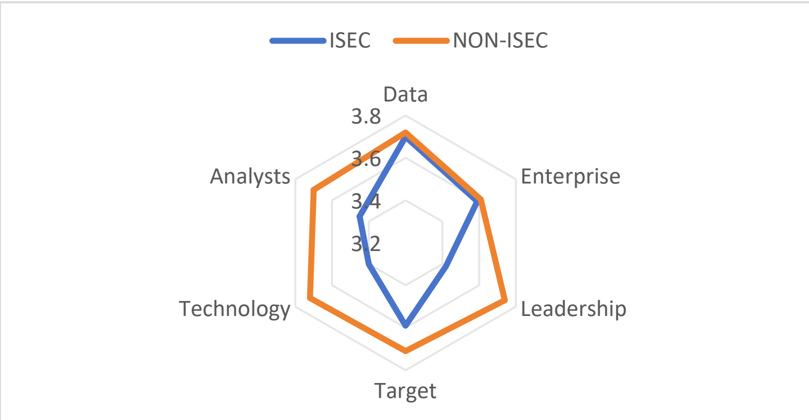
Elements	Group	N	Range	Min	Max	Mean	SD
Data	ISEC	77	4	1	5	3.70	.11
	non-ISEC	77	4	1	5	3.72	.13
Enterprise	ISEC	77	4	1	5	3.59	.10
	non-ISEC	77	4	1	5	3.61	.13
Leadership	ISEC	77	4	1	5	3.42	.12
	non-ISEC	77	4	1	5	3.74	.12
Target	ISEC	77	4	1	5	3.59	.11
	non-ISEC	77	4	1.6	5	3.71	.12
Technology	ISEC	77	4	1	5	3.40	.11
	non-ISEC	77	4	1.6	5	3.72	.11
Analysts	ISEC	77	4	1	5	3.45	.12
	non-ISEC	77	4	1	5	3.76	.12

Notes: The Likert scale from the DELTTA survey corresponds to 1 = Analytically Impaired, 2 = Localized Analytics, 3 = Analytical Aspirations, 4 = Analytical Companies, and 5 = Analytical Competitors (Davenport et al., 2010).

The Likert scale from the DELTTA survey reflects the stages of analytics maturity and competitiveness of different enterprises. For a detailed explanation, please refer to the DELTTA Plus Model & Five Stages of Analytics Maturity: A Primer (Davenport et al., 2010), a research report by the International Institute for Analytics (IIA) that introduced the model and method for assessing and improving analytics maturity.

The BDA readiness is delineated into six distinct elements in Table 4, showing the range, minimum, maximum, mean, and standard deviations of the ISEC and non-ISEC groups. For each element of data, enterprise, leadership, target, technology, and analysts, the non-ISEC faculty group had marginally higher scores than the ISEC group. The smallest difference was in the data element, with ISEC (M = 3.7, SD = .11) and non-ISEC (M = 3.72, SD = .13) demonstrating similar readiness. The largest gap was in the leadership element, where non-ISEC faculty (M = 3.74, SD = .12) scored considerably higher than ISEC faculty (M = 3.42, SD = .12).

Overall, Tables 3 and 4 reveal slightly higher levels of big data analytics readiness among non-ISEC faculty compared to the ISEC faculty across both the composite and individual element scores. The descriptive statistics highlight the readiness areas with room for improvement in the ISEC faculty to match or exceed their non-ISEC peers. Figure 1, the Radar Chart, serves as a visual representation of the data presented in Tables 3 and 4. It graphically depicts the comparative levels of Big Data Analytics (BDA) readiness between the ISEC and non-ISEC faculty members.



Note: Survey reliability

Figure 1: Radar chart for the ISEC and non-ISEC DELTTA BDA readiness

Davenport's (2014) big data readiness assessment and the DELTTA model framework were used as survey tools. Although the reliability of this tool has been validated in multiple studies, this study also attempted to examine the internal consistency of the tool. The internal consistency was analyzed using SPSS software version 26, and Cronbach's alpha coefficients were interpreted according to Table 4.

Table 5: Internal reliability interpretation

Cronbach's alpha	Internal Reliability
$\alpha \geq .90$	Excellent
$.90 > \alpha \geq .80$	Good
$.80 > \alpha \geq .70$	Acceptable
$.70 > \alpha \geq .60$	Questionable
$.60 > \alpha \geq .50$	Poor
$.50 > \alpha$	Unacceptable

Notes: Adapted from Making Sense of Cronbach's Alpha, by Tavakol and Dennick. Copyright 2011 by International Journal of Medical Education.

The full survey had a Cronbach's alpha coefficient of .96, indicating a very high degree of internal consistency. Table 5 shows the coefficients and the internal reliabilities of each element of the DELTTA instrument.

Table 6: Reliability analysis of DELTTA survey: Cronbach's Alpha

Element	Cronbach's Score	Internal Consistency
Data	.90	Excellent
Enterprise	.89	Good
Leadership	.89	Good
Targets	.90	Excellent
Technology	.88	Good
Analytics	.91	Excellent
DELTTA	.96	Excellent

Power Analysis

Before conducting the study, the researcher performed a priori power analysis to determine the minimum sample size needed for the independent samples *t*-test. Based on an effect size of .50, a power level of .80, an alpha level of .05, and one degree of freedom, the power analysis yielded a minimum sample size of 128. The researcher obtained an actual sample size of N = 154 completed responses with no missing data, which exceeded the minimum sample size requirement.

Independent Samples t-Test

The researcher used an independent samples *t*-test to compare the average scores of two groups of faculties on a variable called BDA readiness. BDA readiness was a measure of how ready the teachers were to adopt Big Data Analytics in their teaching practices. The researcher used a questionnaire to measure this variable. The two groups were the ISEC faculty and non-ISEC faculty. The researcher attempted to examine if there was a significant difference in the BDA readiness between the two groups. The statistical significance was calculated using a *p*-value of 0.05 to determine the degree to which the relationship might exist based on a probability of chance. The researcher also verified the assumptions required for the independent samples *t*-test, which are the conditions that the data must meet for the test to be valid and reliable.

Assumptions for the Independent Sample t-Test

The researcher also checked the following assumptions of the independent samples *t*-test, which were (a) level of measurement, each of the parametric approaches assumes that the dependent variable is measured at the interval or ratio level. (b) random sampling, (c) independence of observations, (d) normal distribution, (e) homogeneity of Variance.

Assumption 1. The first assumption is that the dependent variable should be continuous. This assumption was met because the study had one dependent variable (BDA adoption readiness level) that was treated as the interval data. A number of researchers support treating Likert items with 5 or more response categories as interval data, provided certain conditions are met, such as large sample size, normal distribution, and homogeneity of variance (Carifio and Perla, 2007; Norman, 2010). This allows more powerful parametric tests to be used for analysis.

Assumption 2. Random sampling: a snowball non-probability sampling method was used to select 160 respondents from the ISEC and non-ISEC faculty in the ISEC member universities in China, which is a limitation of this study due to the non-fulfillment of assumption 2.

Assumption 3. Independence of observations: the researcher used an independent-sample design, meaning that each respondent belonged to only one group or condition, and other respondents or variables did not influence their responses. The ISEC and non-ISEC teachers were mutually exclusive. This assumption was met.

Assumption 4. Normality distribution: Skewness and kurtosis were used to assess the normality of the data. Their absolute values reflect how close the data are to the normal distribution. One rule is that both skewness and kurtosis should be between -1 and +1, but this rule is too strict and will reject many distributions that are close enough to normal for practical purposes. Another rule is that the absolute values of skewness and kurtosis should be less than 2 and 7, respectively, which is a more reasonable criterion, especially when the sample sizes are medium, which can be loosely defined as between 50 and 300, as this range can effectively identify the normal distributions (Kim, 2013, p. 53).

The skewness and kurtosis of the data of this study were -0.559 and -0.196, respectively, both within the range of -1 and +1, which met the criterion suggested by George and Mallery (2010). This indicated that data distribution of this study was approximately normal, without significant skewness or flatness. Therefore, the normality assumption was met.

Table 7: Descriptive statistics of overall DELTTA scores

Descriptive Statistics									
	N	Min	Ma	Mean	SD	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Total DELTTA	154	1.00	5.00	3.62	.83	-.559	.195	-.196	.389
Valid N (listwise)	154								

Table 7 presents the descriptive statistics for the overall DELTTA scores, offering a quantitative overview of the dataset's distribution. This table encapsulates key statistical measures such as the minimum, maximum, mean, standard deviation, skewness, and kurtosis for the total DELTTA scores across a sample size of 154 participants. The mean score of 3.62 suggests a moderate overall performance, with a standard deviation of .83 indicating variability in the data. The skewness and kurtosis values provide insights into the asymmetry and peakedness of the distribution, respectively. Such descriptive analysis is crucial for understanding the underlying trends and patterns in the DELTTA scores, setting the stage for further inferential statistical examination.

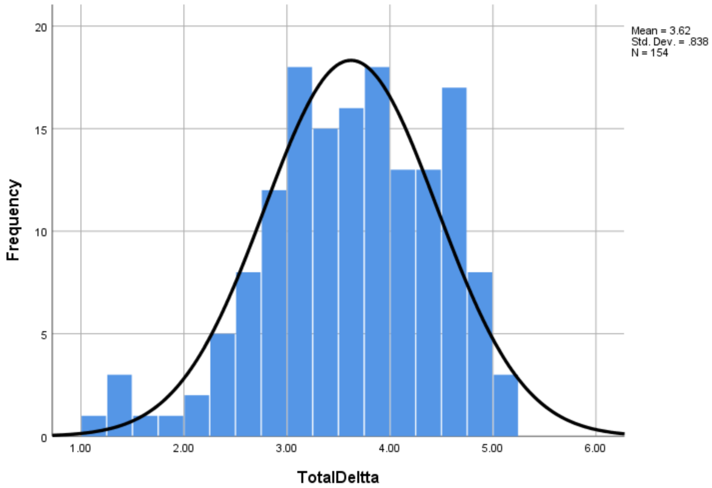


Figure 2: Histogram and normality test for total DELTTA

Figure 2, which includes a histogram and a normality test for the Total DELTTA scores, indicates that the data conforms to a normal distribution. This is evidenced by the bell-shaped curve of the histogram and the normality test results, which likely show a non-significant deviation from normality. Such a distribution allows for the application of parametric statistical tests that assume data normality.

Assumption 5. Homogeneity of variance: The Levene test was applied to check the homogeneity of variance assumption of each sample. Considering the first row of the t-test table, with equal variances, should be used if the Sig. value for Levene's test is greater than .05. The second row of the t-test table, which does not assume equal variances, should be referred to if the significance level of Levene's test is p=.05 or lower.

Levene's tests were performed to check the homogeneity of variances for each pair of groups based on the total DELLTA score and six individual element scores. The results showed that all p-values were greater than .05, indicating that the variances were not significantly different across groups. Therefore, the first row of the t-test table, which assumes equal variances, was utilized for the subsequent analyses. This assumption was met for all comparisons except the enterprise element. The specific statistical results are presented in the following Table 8.

Table 8: Levene's test for equality of variance

DELTTA BDA	Levene's test for equality of variance			
	F	Sig.	t	Df
ISEC and non-ISEC faculty	.19	.66	-1.39	152
Data	2.53	.11	-.15	152
Enterprise*	4.32	.04	-.11	145.85
Leadership	.16	.69	-1.94	152
Targets	.15	.70	-.76	152
Technology	.01	.92	-2.04	152
Analysts	.03	.85	-1.79	152

Notes: N=154 (77 for each ISEC and non-ISEC group. * Values for the enterprise subscale are from Welch t-test (equal variances not assumed) for t-test for equality of means.

Independent t-Test Results of RQ1

This study focuses on the difference in BDA readiness between faculty who are part of the ISEC programs and those who are not. The main question (RQ1) concerns whether there's a statistically significant difference in BDA readiness level between these two faculty groups. Understanding this difference is important to see if being part of ISEC affects a teacher's ability to use BDA.

RQ1: Is there a statistically significant difference between the ISEC and non-ISEC faculty BDA readiness?

Table 9: Two-tailed independent t-Tests for BDA readiness

	t-test for Equality of Mean					95% CI	
Variables	t	df	p value	Mean Difference	Cohen's d	Lower	Upper
ISEC and non-ISEC faculty	-1.39	152	.17	-.19	.23	-.45	.08

An independent-samples *t*-test was conducted to compare the overall BDA readiness scores for ISEC and non-ISEC faculty. There was no statistically significant difference in overall BDA readiness scores for ISEC faculty (M = 3.52, SD = .83) and non-ISEC faculty (M = 3.71, SD =.83; t (152) = -1.38, p =.17, two-tailed). The null hypothesis for RQ1 was not rejected based on the findings. The magnitude of the differences in the means (mean difference = -.186, 95% CI: -.45 to .08) was small (Cohen d =.228). The effect size was calculated by using the online calculator from socscistatistics.com and it was interpreted based on Cohen's (1988) rule of thumb: a value of .20 represents a small effect size; a value of 0.5 represents a medium effect size, and a value of .80 represents a large effect size.

Independent t-Test Results of RQ2

Research Question 2 (RQ2) was aimed to examine if a statistically significant difference exists in the readiness levels for BDA across specific elements - data, enterprise, leadership, targets, technology, and analysts - between the ISEC and the non-ISEC faculty. Identifying these differences is crucial for understanding how ISEC affiliation might influence an educator's proficiency in various BDA components, informing targeted enhancement of BDA capabilities.

RQ2: Is there a statistically significant difference between the ISEC and non-ISEC faculty, and BDA readiness elements individually (data, enterprise, leadership, targets, technology, and analysts)?

Table 10: Independent samples t-test of BDA scores for the ISEC and non-ISEC faculty

	Group	Mean	SD	Mean difference	t	Sig.	Cohen d	95% Lower	CI Upper
Overall	ISEC	3.52	.83	-.19	-1.39	.17	.23	-.45	.08
	non-ISEC	3.71	.83						
Data	ISEC	3.70	.97	-.03	-.15	.88	.02	-.36	-.31
	non-ISEC	3.73	1.12						
Enterprise*	ISEC	3.60	.92	-.02	-.11	.91	.02	-.35	.31
	non-ISEC	3.62	1.13						

continued

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Leadership	ISEC	3.42	1.03	-.32	-1.93	.06	.31	-.65	.01
	non-ISEC	3.74	1.02						
Target	ISEC	3.60	1.01	-.12	-.76	.45	.12	-.45	.2
	non-ISEC	3.72	1.03						
Technology	ISEC	3.40	1	-.32	-2.04	.04	.32	-.64	-.01
	non-ISEC	3.72	.97						
Analysts	ISEC	3.45	1.05	-.31	-1.79	.08	.29	-.65	.03
	non-ISEC	3.76	1.1						

Notes: N=154 (77 for each ISEC and non-ISEC group. * Values for data subscale are from Welch t-test (equal variances not assumed) for t-test for equality of means.

Research Question 2 examined whether there were statistically significant differences in big data analytics (BDA) readiness between the ISEC and non-ISEC faculty across six individual elements: data (ISEC: M = 3.70, SD = 0.97; non-ISEC: M = 3.73, SD = 1.12), enterprise (ISEC: M = 3.60, SD = 0.92; non-ISEC: M = 3.62, SD = 1.13), leadership (ISEC: M = 3.42, SD = 1.03; non-ISEC: M = 3.74, SD = 1.02), targets (ISEC: M = 3.60, SD = 1.01; non-ISEC: M = 3.72, SD = 1.03), technology (ISEC: M = 3.40, SD = 1.00; non-ISEC: M = 3.72, SD = 0.97), and analysts (ISEC: M = 3.45, SD = 1.05; non-ISEC: M = 3.76, SD = 1.10). Independent samples t-tests were conducted to test sets of directional hypotheses.

The *t*-test results indicated no significant differences between the ISEC and non-ISEC faculty for data readiness, enterprise readiness, targets readiness, or analysts' readiness, with all p values > .05. However, there was a significant difference for technology readiness, t (152) = -2.04, p = .04, with non-ISEC faculty scoring higher than the ISEC faculty. The mean differences ranged from -0.03 (data) to -0.32 (leadership), with corresponding small to medium Cohen's d effect sizes from 0.02 to 0.32. The 95% confidence intervals for the non-significant readiness elements all overlapped zero, further indicating a lack of significant differences. For technology readiness, the predominantly negative 95% CI suggests the direction of the significant difference favoring non-ISEC faculty.

5. Discussion and Conclusion

Research Question #1: Descriptive statistics for DELTTA readiness scores show ISEC faculty (M = 3.52, SD = 0.83) scored lower than non-ISEC faculty (M = 3.71, SD = 0.83). An independent-samples t-test found no statistically significant difference in overall BDA readiness scores between ISEC (M = 3.52, SD = 0.83) and non-ISEC faculty (M = 3.71, SD = 0.83; t(152) = -1.38, p = 0.17). The mean difference was -0.186, 95% CI: -0.45 to 0.08, with a small effect size (Cohen's d = 0.228).

Wang (2022) found higher BDA readiness among internationalization program participants, with scores of 0.76, 0.82, and 0.79 for data literacy, technology adoption, and analytical ability, respectively, compared to 0.65, 0.69, and 0.67 for non-participants. This study found no significant readiness advantage for internationalization program participants, suggesting differing methods and samples as potential reasons.

Research Question #2: Independent t-tests examined BDA readiness between ISEC and non-ISEC faculty across six elements: data (ISEC: M = 3.70, SD = 0.97; non-ISEC: M = 3.73, SD = 1.12), enterprise (ISEC: M = 3.60, SD = 0.92; non-ISEC: M = 3.62, SD = 1.13), leadership (ISEC: M = 3.42, SD = 1.03; non-ISEC: M = 3.74, SD = 1.02), targets (ISEC: M = 3.60, SD = 1.01; non-ISEC: M = 3.72, SD = 1.03), technology (ISEC: M = 3.40, SD = 1.00; non-ISEC: M = 3.72, SD

= 0.97), and analysts (ISEC: M = 3.45, SD = 1.05; non-ISEC: M = 3.76, SD = 1.10). There were no significant differences for data, enterprise, targets, and analysts readiness ($p > 0.05$). However, technology readiness was significantly higher for non-ISEC faculty ($t\ (152) = -2.04$, $p = 0.04$).

Tasmin and Huey (2020) found that BDA readiness alone does not predict big data adoption; factors like relative advantage, compatibility, and top management support are crucial. BDA is vital for educational leaders to improve education quality and outcomes, requiring data literacy, analytical skills, organizational management, and political awareness (Datnow and Park, 2014).

Policymakers should support BDA in education through funding, standards, incentives, and data security measures. Collaboration with stakeholders is essential for successful BDA adoption (Bhutoria, 2022). Challenges include inconsistent policies, stakeholder resistance, and ethical issues in data sharing (Selwyn, 2015).

6. Limitations and Future Research Directions

This study's sample was limited to teachers from ISEC member institutions in China, potentially not representing the broader population of teachers in China or globally. The variables were based on the DELTTA framework, possibly missing some aspects of BDA readiness. Causal relationships inferred from statistical analysis may not fully capture actual causal mechanisms. Future studies on BDA readiness in education should adopt rigorous, culturally responsive approaches to fill literature gaps. Researchers should recruit diverse samples across educational contexts, disciplines, career stages, and cultural groups. Comprehensive sampling can clarify the generalizability of findings and uncover nuanced readiness variations based on sociocultural dynamics and individual-systemic factors. Adopting critical, inclusive lenses that account for privilege, oppression, and social constructions of technology can elucidate engagement equitably.

Studies should explore multidimensional relationships between readiness and related constructs to assess validity and generalizability. Testing hypothesized antecedents, moderators, mediators, and outcomes can provide holistic BDA readiness models. Mixed methods combining surveys, interviews, ethnography, and experiments are crucial for capturing cognitive, motivational, and behavioral processes influencing engagement. Integrating qualitative insights into systemic barriers and cultural meanings is vital for contextualizing quantitative patterns. Researchers should minimize limitations around sampling, measurement errors, and analytic techniques, using strategies to strengthen validity and rigor.

In summary, expanding diverse samples, investigating multidimensional relationships, and leveraging mixed methods are key future directions. Such rigorous, culturally responsive research will empower diverse faculty by uncovering nuanced insights to guide the development of inclusive BDA policies and environments in our increasingly data-driven educational landscape. The overall investigation into BDA readiness revealed no statistically significant differences between ISEC and non-ISEC faculty, suggesting uniform preparedness across both domains under the same organizational leadership. The only discernible disparity was in Technology Readiness, with non-ISEC faculty demonstrating superior proficiency, highlighting the need for targeted interventions to ensure uniform BDA readiness across diverse academic domains.

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