Journal of Contemporary Issues and Thought
ISSN 2232-0032/ e-ISSN 0128-0481/ Vol 15, Issue 2, 2025 (49-62)

Demographic Dynamics of Data Analytics Readiness: A Comparative Exploration of Chinese Higher Education Faculty?

Han Yu*

Department Guizhou University of Commerce,
No. 1, 26th Avenue, Maijia Town, Baiyun District, Guiyang, China.
**Email: 393503694@qq.com*

Abstract

Amid the growing imperative for digital transformation in higher education, the readiness of academic faculty to adopt data analytics tools remains underexplored, particularly in the Chinese context. This study investigates the influence of demographic and professional characteristics on faculty readiness for big data analytics (BDA) across International Scholarly Exchange Curriculum (ISEC) and non-ISEC institutions. The primary objective is to examine differences in BDA readiness across variables such as ISEC affiliation, gender, professional rank, and educational background. Using a non-experimental causal-comparative design, data were collected from 154 full-time faculty members across 10 Chinese universities. A modified DELTA+ model served as the assessment framework, covering six key dimensions of analytics readiness: data, enterprise, leadership, targets, technology, and analysts. Statistical analysis using t-tests and two-way ANOVA revealed that while most readiness dimensions did not significantly differ, technology readiness was significantly higher among non-ISEC faculty. Gender, rank, and education showed no main effects, though a significant interaction between ISEC status and education was observed. These findings underscore the complexity of technological readiness and suggest that institutional affiliation and educational background interact in shaping analytics capabilities. The study calls for targeted institutional policies and further research to refine professional development strategies in higher education.

Keywords: Big data; DELTA; Higher education

1. Introduction

In the contemporary landscape of higher education, digital transformation has emerged as a critical catalyst for institutional evolution and pedagogical innovation (Daniel, 2017). The COVID-19 pandemic precipitated an unprecedented technological acceleration, compelling educational institutions to rapidly recalibrate their technological infrastructures and pedagogical methodologies (Daniel, 2020; Bao, 2020).

The International Scholarly Exchange Curriculum (ISEC), strategically positioned within China's educational modernization framework, represents a sophisticated institutional transformation model. Affiliated with the China Scholarship Council (CSC) and embedded in the "Education Modernization 2035 Plan," ISEC strategically targets local and provincial higher education institutions. Unlike traditional educational approaches, ISEC adopts a comprehensive internationalization strategy that emphasizes systematic professional development through structured training and rigorous assessment protocols.

Theoretical perspectives on technological adoption provide essential conceptual foundations for understanding this transformative process. The Unified Theory of Acceptance and Use of Technology (UTAUT) framework elucidates the complex psychological mechanisms underlying technological integration (Venkatesh et al., 2012). Empirical research consistently demonstrates that individual differences—particularly age, gender, and professional rank—significantly moderate technology acceptance rates (Compeau and Higgins, 1995; Gibson, 2017).

Building upon Gibson's (2017) insights into technological competence, this study cautiously explores the potential variations in faculty readiness for data analytics tools. Through a non-experimental causal-comparative design involving 154 faculty members across 10 Chinese universities, this study aims to tentatively investigate the interactions between demographic factors and technological preparedness. This research seeks to develop preliminary insights into the mechanisms of technological adoption, faculty development strategies, and the complex relationships between individual characteristics and technological readiness.

Methodologically, a modified DELTA+ assessment instrument was leveraged, characterized by enhanced validity and reliability, to capture the multidimensional nature of technological readiness. Our mixed-methods approach integrates quantitative analysis with contextual qualitative insights, providing a comprehensive understanding of technological adoption dynamics.

The study's contributions tentatively extend beyond traditional academic discourse, offering preliminary attempt into potential interventions across multiple domains. By carefully examining faculty training strategies, cross-cultural learning environment design, and potential pathways for digital transformation in higher education, our research modestly bridges theoretical frameworks with empirical evidence. While acknowledging the inherent limitations of our study, we aim to contribute to the emerging scholarship on technological integration in global higher education, with a focused exploration of the complex Chinese educational context. Our findings suggest potential mechanisms for understanding technological adoption, recognizing the need for further research to validate and expand these initial observations.

2. Digital Transformation in Higher Education and the Theoretical Synthesis Framework

The landscape of digital transformation in higher education represents a complex, multifaceted phenomenon that transcends simplistic technological implementation. Arviansyah et al. (2024) critically illuminates this transformation as a profound reconfiguration of institutional logics and practice paradigms, challenging traditional conceptualizations of technological innovation. The Technology-Organization-Environment (TOE) framework emerges as a pivotal theoretical lens, with Baker (2011) systematically articulating its foundations and Hiran and Henten (2020) empirically demonstrating the contextual complexity of technological integration in educational settings.

Theoretical perspectives from innovation diffusion and critical technology studies provide nuanced insights into this transformative process. Rogers' (1962) seminal work on innovation diffusion reveals the complex mechanisms of technological propagation. Simultaneously, Bijker (1997) and Feenberg (2012) challenge technological determinism, conceptualizing technological artifacts as socially constructed entities embedded with power relations and cultural meanings. Çelik (2024) synthesizes these perspectives, demonstrating how technological innovation simultaneously shapes and is shaped by organizational practices, with Markus (2004) and Orlikowski (2000) particularly emphasizing the dialectical relationship between technological systems and human agency.

The critical examination of digital transformation extends beyond mere technological implementation, revealing a complex interplay of social, organizational, and technological dynamics. Noble's (2017) historical sociological analysis and Selwyn's (2019) critical investigation of artificial intelligence in education underscore the profound institutional implications of technological innovation. Greenhalgh et al. (2004) provide a systematic review of innovation diffusion, while Chatterjee et al. (2024) offer a sophisticated framework exploring the intricate relationships between technological capabilities, organizational turbulence, and management support.

Ultimately, digital transformation in higher education emerges as a continuous process of institutional reimagination. It demands a sophisticated theoretical approach that transcends technological instrumentalism, focusing instead on the complex interplay between technological artifacts, organizational practices, and human agency. The theoretical synthesis reveals this transformation not as a predetermined trajectory, but as a dynamic, contextually embedded process of institutional reconfiguration that requires continuous critical reflection and adaptive theoretical frameworks. This comprehensive analysis illuminates digital transformation as a multidimensional phenomenon that fundamentally challenges existing institutional logics. It represents a critical juncture where technological potential, institutional constraints, and social dynamics converge, requiring researchers and institutional leaders to develop nuanced, flexible theoretical frameworks for understanding technological change in higher education.

Recognizing the complexity of digital transformation in higher education, five theoretical frameworks for digital transformation were analyzed: DAVCM, DACM, DAMM, DALM, and DELTA Model. Each model reveals distinct limitations: DAVCM oversimplifies complexity, DACM lacks empirical support, DAMM neglects technological dynamics, and DALM remains overly abstract (Curry, 2016; Király and Zdonek, 2020). Adopting Davenport et al.'s (2010) DELTA model, this study leverages a comprehensive framework integrating data, enterprise, leadership, technology, targets, and analysts to ensure strategic alignment with institutional transformation 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, methods of data analysis	Over-simplifies, ignore environmental influences
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, ignores 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
DELTA Model	Evaluates data, enterprise, leadership, targets, analysts	Comprehensive, practical, adaptive, 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 and data.

3. Methodology

Employing a causal-comparative research design recommended by Campbell and Stanley (1963), this study systematically explored differences in Big Data Analytics (BDA) readiness between ISEC and non-ISEC faculty without direct variable manipulation, enabling precise identification of significant group variations (Proudfoot et al., 2018). The research was theoretically grounded in the DELTA+ model (Davenport et al., 2010), which assesses BDA readiness across six critical dimensions: data, enterprise, leadership, targets, technology, and analysts. These dimensions provide a nuanced framework for understanding technological readiness in educational contexts.

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

Four research questions guided the investigation:
- RQ1: Are there significant differences in BDA readiness elements between ISEC and non-ISEC faculty?
- RQ2: Are there significant differences in BDA readiness based on gender?
- RQ3: Are there significant differences in BDA readiness based on professional rank?
- RQ4: Are there significant differences in BDA readiness based on educational background?

Sample size determination utilized G*Power 3.1.9.7, establishing parameters of a medium effect size (0.5), significance level of 0.05, and statistical power of 0.80. This approach yielded a minimum requirement of 64 participants per group, with the study ultimately recruiting 160 participants to ensure robust analytical depth. The sampling strategy employed stratified random sampling, targeting full-time faculty members across multiple Chinese universities. Careful selection criteria ensured representation from ISEC and non-ISEC programs, maintaining methodological integrity.

The measurement instrument—a modified DELTA+ BDA Readiness Assessment—utilized a 5-point Likert scale. Rigorous validation processes, including expert panel review, yielded a Cronbach's α of 0.87, demonstrating strong instrument reliability. Statistical analyses integrated descriptive and inferential techniques, including independent samples t-tests and one-way ANOVA. These methods enabled systematic examination of potential differences in BDA readiness across demographic and professional characteristic:

4. Data Analysis

Participants' Demographic Profiles

This section demonstrates participant demographic profiles based on the survey responses from 154 faculty 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

Note: 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, 2014; 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, 2014; 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.

Independent t-Test Results of RQ1

Research Question 1 (RQ1) 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.

RQ1: 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 5: 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						
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 1 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.

Two-way ANOVA Analysis Results of RQ2

RQ2: Is there a statistically significant difference in BDA Readiness between ISEC faculty and non-ISEC faculty based on gender?

Table 6: Descriptive statistics of overall DELTTA BDA scores for ISEC and non-ISEC faculty based on gender

Group	Gender	Mean	Std. Deviation	N
ISEC	Male	3.49	0.80	37
	Female	3.56	0.87	40
	Total	3.53	0.83	77
Non-ISEC	Male	3.84	0.79	44
	Female	3.54	0.88	33
	Total	3.71	0.84	77
Total	Male	3.68	0.81	81

	Female	3.55	0.87	73
	Total	3.62	0.84	154

Table 7: Two-way ANOVA of overall DELTTA BDA scores for ISEC and non-ISEC faculty based on gender

Source	F	Sig.	Partial Eta Squared
ISEC Non-ISEC	1.517	0.22	0.01
Gender	0.723	0.396	0.005
ISEC Non-ISEC*Gender	1.95	0.165	0.013

**Indicates interaction effect*

Research Question 2 (RQ2) examined whether there was a statistically significant difference in overall big data analytics BDA readiness between ISEC and non-ISEC faculty based on gender. A two-way ANOVA was conducted with two between-subjects factors - ISEC status (ISEC vs non-ISEC) and gender (male vs female).

The descriptive statistics showed that male faculty in the non-ISEC group had the highest overall BDA readiness score ($M = 3.84$, $SD = 0.79$, $n = 44$), while male faculty in the ISEC group had the lowest score ($M = 3.49$, $SD = 0.80$, $n = 37$).

Levene's test verified the assumption of homogeneity of variances was met, $F(3, 150) = 0.095$, $p = .963$. The two-way ANOVA results indicated no significant main effect for ISEC status, $F(1, 150) = 1.517$, $p = .22$, partial $\eta 2 = .010$, or for gender, $F(1, 150) = 0.723$, $p = .396$, partial $\eta 2 = .005$. The interaction effect between ISEC status and gender was also not significant, $F(1, 150) = 1.95$, $p = .165$, partial $\eta 2 = .013$.

In summary, the findings for RQ3 failed to reject the null hypothesis as there were no significant differences in overall BDA readiness between ISEC and non-ISEC faculty when accounting for gender. This signifies that gender may not be a powerful factor influencing BDA readiness levels in this sample. Further research with larger sample sizes may be warranted to fully examine potential interaction effects.

Two-way ANOVA Analysis Results of RQ3

RQ3: Is there a statistically significant difference in BDA Readiness between the ISEC and non-ISEC faculty based on professional rank?

Table 8: Descriptive statistics of overall DELTTA BDA scores for ISEC and non-ISEC faculty based on professional rank

Groups	Prank	Mean	Std. Deviation	N
ISEC	TA	3.27	0.28	2
	Lecturer	3.44	0.83	37
	Associate Prof	3.67	0.95	28
	Prof	3.52	0.56	10
	Total	3.53	0.83	77
Non-ISEC	TA	3.47	0.87	4
	Lecturer	3.83	0.79	46
	Associate Prof	3.52	0.95	23
	Prof	3.75	0.65	4
	Total	3.71	0.84	77
Total	TA	3.40	0.69	6
	Lecturer	3.66	0.82	83
	Associate Prof	3.60	0.95	51
	Prof	3.59	0.57	14
	Total	3.62	0.84	154

Table 9: Two-way ANOVA of overall DELTTA BDA scores for ISEC and non-ISEC faculty Based on professional rank

Source	F	Sig.	Partial Eta Squared
ISEC Non-ISEC	.517	.473	.004
Professional Rank	1.183	.908	.004
ISEC Non-ISEC*ProfRank	1.081	.359	.022

**Indicates interaction effect*

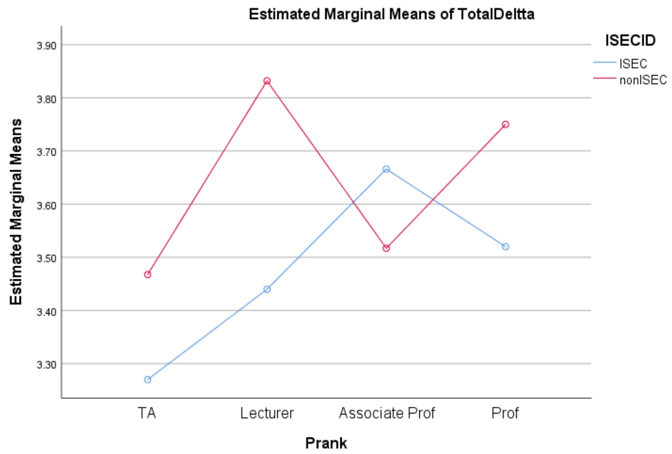

Figure 1: Profile plot based on professional rank

Research Question 3 examined whether there were significant differences in big data analytics (BDA) readiness between ISEC and non-ISEC faculty based on professional rank (teaching assistant, lecturer, associate professor, professor). A two-way ANOVA was conducted with two between-subjects factors - ISEC status and professional rank.

The descriptive statistics showed that mean BDA readiness scores were relatively similar across professional ranks, ranging from 3.40 (teaching assistants) to 3.59 (professors) in the total sample. Amongst ISEC faculty, associate professors had the highest readiness (M = 3.67, SD = .95, n = 28), while teaching assistants had the lowest (M = 3.27, SD = .28, n = 2). For non-ISEC faculty, lecturers showed the highest readiness (M = 3.83, SD = .79, n = 4), and teaching assistants had the lowest scores (M = 3.47, SD = .87, n = 4).

Levene's test verified that the assumption of homogeneity of variances was met, F (7, 146) = 1.067, p = .388. The two-way ANOVA revealed no significant main effect for ISEC status, F (1, 146) = 0.517, p = .473, partial η2 = .004, indicating no significant difference in overall BDA readiness between ISEC (M = 3.53, SD = 0.83) and non-ISEC (M = 3.71, SD = 0.83) faculty. There was also no significant main effect for professional rank, F (3, 146) = 0.183, p = .908, partial η2 = .004, suggesting no significant differences in BDA readiness across the ranks. Furthermore, the interaction between ISEC status and professional rank was non-significant, F (3, 146) = 1.081, p = .359, partial η2 = .022, signifying that the effect of ISEC status did not differ across ranks.

Since the ANOVA results were not significant, that is, the p-values of the main effects or interaction effects were all greater than the significance level (usually 0.05), there was no need to conduct a post hoc test, because the purpose of these comparisons was to find out which groups had significant differences, and the ANOVA had already shown that there were no significant differences. Performing post hoc multiple comparisons might increase the risk of

Type I error, which is rejecting the null hypothesis erroneously, thinking that there were differences.

The profile plot (Figure 1) also displayed no significant interaction effect between ISEC status and professional rank. The plot showed relatively parallel lines for ISEC and non-ISEC faculty groups across the ranks of teaching assistant, lecturer, associate professor, and professor. The lack of crossover interaction effects further supports the non-significant difference in BDA readiness between ISEC and non-ISEC across professional ranks.

The results for RQ3 failed to reject the null hypothesis, as the two-way ANOVA found no statistically significant differences in overall BDA readiness between ISEC and non-ISEC faculty based on professional rank. These findings indicate professional rank may not be a powerful variable influencing BDA readiness among this particular faculty sample. In addition, further examination using Cohen's d effect sizes revealed no potential practical differences between some ranks. In summary, the non-significant statistical findings should be interpreted cautiously, as the small and imbalanced rank group sizes likely limited statistical power.

Two-way ANOVA Analysis Results of RQ4

RQ4: Is there a statistically significant difference in BDA Readiness between the ISEC and non-ISEC faculty based on their educational background?

Table 10: Descriptive statistics of overall DELTTA BDA scores for ISEC and non-ISEC faculty based on educational background

Group	Edu background	Mean	Std. Deviation	N
ISEC	BA	3.32	1.70	3
	Master	3.79	0.60	48
	Ph.D.	3.08	0.93	26
	Total	3.53	0.83	77
Non-ISEC	BA	3.43	-	1
	Master	3.66	0.84	54
	Ph.D.	3.87	0.83	22
	Total	3.71	0.84	77
Total	BA	3.35	1.39	4
	Master	3.72	0.74	102
	Ph.D.	3.44	0.96	48
	Total	3.62	0.84	154

Note: Categories with one sample do not have a standard deviation.

Table 11: Two-way ANOVA of overall DELTTA BDA scores for ISEC and non-ISEC faculty Based on educational background

Source	F	Sig.	Partial Eta Squared
ISEC Non-ISEC	.624	.431	.004
Edu Background	1.695	.187	.022
ISEC Non-ISEC*EduBack	5.261	.006	.066

**Indicates interaction effect*

Table 12: Levene's test of equality of error variances for BDA readiness by ISEC groups and educational background

Levene's Test of Equality of Error Variances[a,b]					
		Levene Statistic	df1	df2	Sig.
TotalDeltta	Based on Mean	2.969	4	148	.021
	Based on Median	1.923	4	148	.110
	Based on Median and with adjusted df	1.923	4	83.521	.114
	Based on trimmed mean	2.876	4	148	.025

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Dependent variable: TotalDeltta
b. Design: Intercept + ISECID + eduback + ISECID * eduback

Research Question 4 examined whether there were significant differences in big data analytics (BDA) readiness between ISEC and non-ISEC faculty based on educational background (BA, Master's, Ph.D.). A two-way ANOVA was conducted with two between-subjects factors – ISEC status and education level.

The descriptive statistics showed educational background had varying effects on mean BDA readiness scores for ISEC versus non-ISEC groups. Amongst ISEC faculty, those with a Master's degree had the highest readiness (M = 3.79, SD = .60, n = 48), while Ph.D. holders had the lowest (M = 3.08, SD = .93, n = 26). For non-ISEC faculty, Ph.D. holders displayed the highest readiness (M = 3.87, SD = .83, n = 22), compared to Master's (M = 3.66, SD = .84, n = 54) and BA (M = 3.43, n = 1).

Levene's test showed the assumption of homogeneity of variances was violated, F (4, 148) = 2.969, p = .021. The two-way ANOVA revealed no significant main effect for ISEC status, F (1, 148) = 0.624, p = .431, partial $\eta 2$ = .004. There was also no significant main effect for education level, F (2, 148) = 1.695, p = .187, partial $\eta 2$ = .022. However, a significant interaction effect was found between ISEC status and education level, F (2, 148) = 5.261, p = .006, partial $\eta 2$ = .066. Since Levene's test showed that the assumption of homogeneity of variance was violated, a more stringent significance level (.01) was adopted to evaluate the ANOVA results, to reduce the risk of type I error, the p-value was still = .021. Therefore, the two-way ANOVA on research question 5 was discontinued.

5. Discussion and Conclusions

The investigation of Big Data Analytics (BDA) readiness among ISEC and non-ISEC faculty reveals nuanced insights into technological preparedness across multiple dimensions. While most BDA readiness elements showed no statistically significant differences, technology readiness emerged as a critical differentiating factor between ISEC and non-ISEC faculty. Non-ISEC faculty demonstrated significantly higher technology readiness (t(152) = -2.04, p = 0.04), challenging conventional assumptions about technological capabilities across academic disciplines. This finding aligns with Tasmin and Huey's (2020) research, which emphasizes that BDA readiness is not merely about technological infrastructure but involves complex factors such as relative advantage, compatibility, and organizational support. The finding suggests that technological competence in the digital era transcends generational boundaries, indicating a more nuanced relationship between professional experience and technological adaptability.

Gender analysis revealed no significant differences in BDA readiness, highlighting the importance of moving beyond simplistic demographic categorizations. While Al-Rahmi et al.

(2019) found gender to be a significant moderator in technology acceptance in a Saudi Arabian context, this study's results diverge. As Connell (2013) argues, gender is a complex social structure formed within specific cultural contexts and should not be viewed as a singular, static attribute. The findings underscore the need for intersectional approaches that consider gender's interaction with other social factors like education, work experience, and self-efficacy.

Professional rank did not significantly impact BDA readiness, suggesting that technological competence is more closely linked to individual motivation, institutional culture, and continuous learning opportunities. Adrian et al. (2017) had hypothesized that higher-ranked faculty might be more likely to adopt BDA due to greater knowledge and resources. However, this study's results caution against such linear assumptions. As Morley et al. (2020) suggest, research should adopt inclusive perspectives that value diverse expertise across academic hierarchies and career stages. This study extends the DELTA+ model by revealing the complex interactions between disciplinary backgrounds and technological readiness, demonstrating that Big Data Analytics (BDA) is crucial for educational leaders to improve educational quality (Datnow and Park, 2014).

6. Limitation and Future Research

While acknowledging limitations of geographical and institutional specificity, the research challenges simplistic assumptions about technological capabilities by emphasizing a context-sensitive, holistic approach to technological development (Bhutoria, 2022). Recognizing the multifaceted nature of technological preparedness, future research should explore cross-institutional comparisons, longitudinal technological adaptation patterns, and deeper analyses of organizational factors influencing BDA readiness. Policymakers are urged to develop targeted funding mechanisms, establish clear technological standards, create incentive structures, and address critical data security and ethical concerns, thereby moving beyond demographic categorizations to foster a more nuanced understanding of technological competence in higher education (Selwyn, 2015).

Future research could significantly advance the understanding of BDA readiness by developing more comprehensive, culturally responsive methodological approaches. Researchers are encouraged to transcend traditional sampling strategies, recruiting diverse participants across multiple educational contexts, disciplinary domains, and cultural configurations. By adopting mixed-methods designs that integrate quantitative rigor with qualitative depth, future studies could explore the complex cognitive, motivational, and institutional factors mediating technological competence, thereby enhancing the generalizability of findings and unveiling nuanced technological engagement patterns.

Subsequent investigations might productively employ critical, intersectional perspectives to examine technological readiness. Scholars are recommended to interrogate the complex interactions between individual agency and institutional structures, accounting for power dynamics, social constructions, and systemic inequities. Future research could benefit from implementing longitudinal research designs, advanced mixed-methods approaches, and sophisticated analytical frameworks that move beyond linear, deterministic models. By developing context-sensitive, equity-focused research strategies, subsequent studies could generate transformative insights into the dynamic, socially embedded nature of technological preparedness across diverse academic landscapes.

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