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Technology, Organization and Environment as Strategic Factors of Big Data Analytics Readiness and Acquisition Intention to adopt Big Data Analytics in Malaysian Libraries

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Abstract
Libraries can learn BD analytics. The report examines Malaysian library big data analytics for new research. Complete subject debate recordings enhance comprehension. Adopt TOE-BDA. Multiple research gaps led this study. Malaysian libraries use new BDA. Not predictive, most data analysis is descriptive. Libraries and information science rarely use big data analytics (BDA). Initial measurement analysis revealed framework concerns. TOE, BDAR, and big data analytics acquisition propensity were linked in structural model analysis. This study made three empirical, theoretical, and practical contributions. The study empirically tests Malaysian libraries' relationship. Future researchers may explore TOE, BDA, and AITABDA using the paradigm. Measure TOE/BDAR.

Keywords: big data analytics readiness (BDAR); TOE factors readiness; library science; data analytics

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1.0 Introduction

Because of their global availability and internet access, libraries are also monitoring data richness. Digital devices, more digital source kinds, and evolving data collection, recording, and analysis technology are also part of it (Heidron, 2011). Blummer & Kenton (2018) claimed that BD modifications and full use influence libraries' survival since they must find new services to be competitive. Additionally, library administration used data to assess user patterns and demand. Libraries have moved on to complex data analysis, including Big Data Analytics (BDA) capabilities (Frederick, 2017).

Many studies, including He & Zhang (2016), Jantti & Heath (2016), Chen et al. (2015), and Rajasekar (2014), demonstrate the effectiveness of Big Data Analytics (BDA) in analysing the overall performance of organisations, businesses, and sectors. The above studies also investigated using Big Data Analytics (BDA) to improve library operations in Malaysia. The present study also examines big

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data (BD) roles in several library services, including academic libraries. Acquisition, services, references, automation, user satisfaction surveys, and research data support are examples. These duties make up most of Malaysian libraries' normal tasks.

2.0 Literature Review

Malaysia has academic, public, and school libraries. Many types of libraries perform similar services and processes. Ahmad (2018) claims that all libraries supply similar data daily. These include purchasing, digitised content, online sources, physical visitors, online visitors, physical loans, online loans, library membership, admission, publication data, etc. Due to their volume and capacity, these data can be examined using BDA. Except for school libraries, this area lacks a library management system to administer daily library operations.

Accordingly, Chang (2018) found that modern libraries need a new way for assessing service quality that uses analytical knowledge and applications. Ahmad (2018) claims that Malaysian libraries rarely use the BDA for performance monitoring. Blummer & Kenton (2018) found that many libraries lack a clear vision and knowledge of Big Data Analytics (BDA) and its technical application. Several factors affect Malaysia Libraries' BDA use. Library readiness, technological readiness, human readiness, analytic capability, culture, environment, data management process, system quality, and data and information quality are these factors (Adrian et al., 2017).

2.1 Big Data in Malaysia Libraries (MLs)

Malaysian libraries have studied big data through data mining. This entails analysing borrowing activity from the library's database to determine book expenditure and other ROI service (Karno, 2022). Due to the Fourth Industrial Revolution (IR 4.0), which integrates technology and robots into various industries, the industrial sector needs a comprehensive suite of tools to oversee and evaluate company operations. The Malaysian government used MAMPU to integrate big data in public administration in 2017. Libraries were encouraged to use statistics to evaluate each acquired item and its use by library customers. The these circumstances have led libraries to actively use data (Karno, 2022).

Karno (2022) also claims that Malaysian libraries have acknowledged the everyday generation of large amounts of data because to the COVID-19 pandemic's increased demand for online services. Perpustakaan Negara Malaysia on 2021 report found that data volumes for information and communication technology (ICT) services in all Malaysian libraries increase annually. The Perpustakaan Sultanah Zanariah, Universiti Teknologi Malaysia (UTM), Selangor Public Library, and UTP Information Resources Centre are among Malaysia's libraries. Data is used to evaluate each library's performance. More libraries use data to evaluate performance. The library's methodology is descriptive analysis alone. Putrawan (2015) suggests using predictive analysis to improve reporting. The library can then make better decisions about its future direction.

2.2 5Vs of Big Data

Big Data analyses and extracts data from large, complicated sources. Data volumes that develop rapidly are often called "exponential growth". Conventional data management tools and techniques cannot efficiently process and store this data due to its size and complexity. Many examples demonstrate massive data. Various sectors use social media and e-commerce data to enhance operations. Over the past year, BD has become a new area for IT-enabled innovations, and BD and analytics may rise in use and capability. Beyond that, business intelligence (BD) and analytics are growing in IT (Karno, 2022).

Big data includes data mining, analysis, storage, and visualisation. "Big data" refers to data collection and processing methods (Rajasekar, 2014). Karno (2022) and Rajasekar (2014) found that the library has big data characteristics, allowing it to monitor all operating activities. Big data is evaluated using the 5 Vs: volume, velocity, value, variety, and veracity:

i) The term "volume" refers to available data. GB, ZB, and YB are used to quantify data volume. Based on market trends, data volume is expected to rise significantly in the future years.

ii) Velocity describes data processing speed. High velocity is crucial for large-scale data processing efficiency and effectiveness. This phenomenon involves measuring variation, heightened activity, and integrating incoming datasets.

iii) The term "value" refers to the benefits an organisation gains from using data. Does it fit your company's goals? Does it advance your company? One of the most important aspects of enormous data is its importance.

iv) The concept of "variety" refers to the varied classifications of vast data. Big data's performance impact is a major issue. Organising diverse data is crucial for effective management. Variety is the variety of data from multiple sources.

v) Veracity refers to the accuracy and dependability of collected data. Big Data's low authenticity can hurt results.

Big data traits and descriptors show that the library has the needed features. Some complete strategies are enough to employ big data analysis in Malaysian library management.

2.3 Theories of Big Data Analytic & Technology Capability Readiness

According to Parasuraman (2000), "technology capability readiness," or "TCR," is a person's willingness to adopt new technology. TCR is the individual's view and daily use of technology items and services. A second aspect that determines the TCR is if new technologies that can help firm employees and teams achieve their professional goals are available in the customers' territory. New technologies have changed how advantages are communicated. Other than that, technology makes administrative and other services easier to obtain, increasing profitability and efficiency (Yunis et al., 2012).

Rapid technological growth and convergence have changed culture, society, and the economy. According to Kalema & Mokgadi (2017), anomalous technological readiness allows organisations to manage business electronically. This reduces turnaround time, improves service delivery, improves item selection, boosts global competitiveness, expands market reach, lowers costs, provides faster and limitless access to new clients and suppliers, and deepens data. Data and interchange technologies are invaluable to the economy, and major and small institutions recognise this. This applies to both sorts of institutions (Kalema & Mokgadi, 2017).

2.4 Technology, Organization & Environment (TOE) Framework Structure

These techniques naturally prompt consideration on how knowledge development and cooperation are crucial to information security management's human variable. However, we understand how important it is to view individuals as potential risk promoters in the workplace because this helps identify and address security breaches faster.

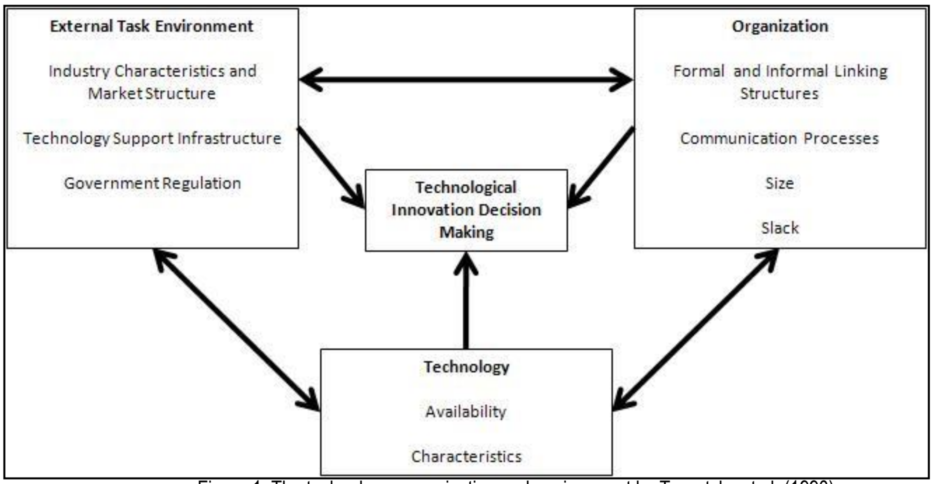

Figure 1: The technology, organization and environment by Tornatzky et al. (1990)

2.5 Theoretical Framework and Hypothesis Development

The TOE determines BDAR acceptability, says one study. Several TOE-based studies examine how various factors affect technology adoption. A developmental BDAR concept that captures these variables is needed to coordinate technological, organisational, and environmental aspects on BDA uptake. BDAR needs development:

i) Technology evaluates ML's BDA compatibility. This build meets library technology evaluation. This build examines the libraries' ICT infrastructure, data reliability, security, and scalability.

ii) Library management support analyses organisation while choosing new technology. Operational ML impact is easy. The build shows magnitude, budgeting, and magnitude.

iii) Environment factors look at the MLs users and services offered, change management, and culture. An outer element that can be considered for BDAR is change management, culture, and talents.

Every activity—public or private—develops new strategies and methods as data accumulates (Kalema & Mokgadi, 2017). Katal et al. (2013) stated that while some public sectors appear to accept that BDA usage will be increasingly effective, beneficial, and have different effects across many organisations, their hidden concern is an absence of devices and well-trained staff to use BDA legitimately According to Ali et al. (2016), Klievink et al. (2017) and Romijn (2014), every public and private department must create a BDA action plan. Figure 3 shows the proposed research model, which connects TOE main factors to BDAR in MLs and examines BDA acquisition intention using structure determinants from Kalema & Mokgadi (2017) and Tornatzky et al. (1990) TOE systems to build organisation, technology, and environment:

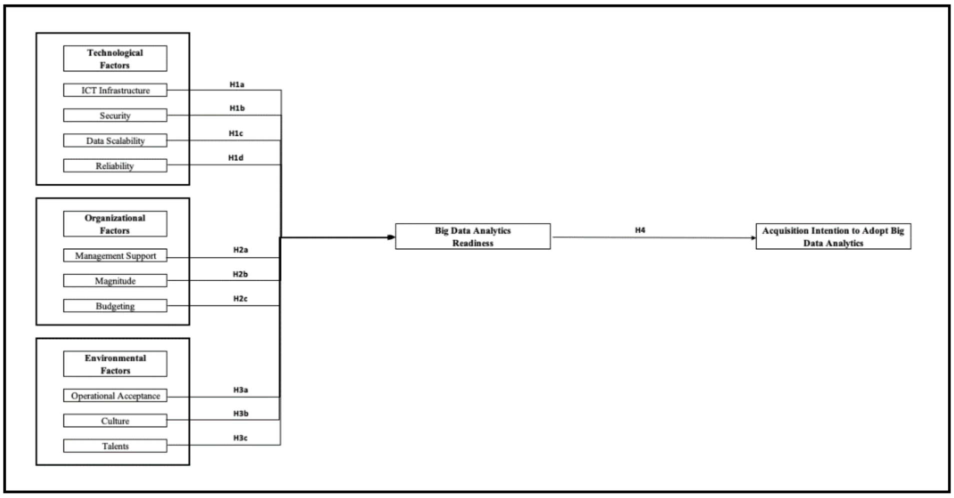

Figure 2: The Proposed Research Model for BDAR and Acquisition Intention to Adopt BDA in Malaysia Libraries

2.6 Hypothesis Statement

Technology, organisation, and environment demands are met by the TOE framework for ML BDAR adoption study. BDAR adoption may be affected by eleven theories and components: management support, magnitude, budgeting, strategies, talents, ICT infrastructure, security, scalability, data dependability, operational acceptance, and culture.

2.6.1 Technology Factors

Park et al. (2014)advise adding novel substances to BDA applications. The TAM hypothesis of Kalema & Mokgadi (2017) claims that ICT infrastructure, data security, scalability, and reliability affect technological dispersion.

To integrate BDA, library HR must manage technical talents. Websites, databases, and computers are secure (Li et al., 2017). Apart from that, data security prevents corruption as said Klievink et al. (2017). Government agencies with sensitive data need security. Data security guarantees ML BDA installation and availability.

Long-term data storage requires scalability. The organisation evaluates ROI and performance using 5–10-year data. Data reliability is accuracy and completeness that can be processed anytime. Technical readiness affects BDAR, as hypothesized:

H1a: ICT infrastructure contributes to BDAR.
H1b: Security contributes to BDAR.
H1c: Data scalability contributes to BDAR.
H1d: Reliability contributes to BDAR.

2.6.2 Organization Factors

The data librarian or data scientist is a crucial new role in MLs since BDA acceptance, demonstrating the close association between BDAR adoption and thought library size depended on printed and non-printed collection development and organisation population. Concurred on that libraries have long handled a lot of data and are now inspired to manage another type, where organisation size often affects source accessibility. Due of its larger collection and population, the library can create more analytics data. Extra data can enhance BDAR adoption.

Budgeting capability is an organization's BDA presentation and use budget (Cao et al., 2014). Budgets are high for BDA ML adoption. Budgetary constraints may prevent libraries from adopting BDA:

H2a: Management support contributes to BDAR.
H2b: Magnitude contributes to BDAR.
H2c: Budgeting contributes to BDAR

2.6.3 Environment Factors

Weiner (2009) defined environmental readiness as staff and library change duty and viability. Workers like eco-friendly ML libraries. Use is usually a 'group sport,' therefore problems occur when certain vibrations favour use and others don't. Weiner (2009) discovered that environmental factors greatly impact operational acceptance and culture. Operational acceptance aids business change adaptation for individuals, groups, and organisations. Changes include technical, process, and user tendency changes; weight from new service contestants; acquisitions, mergers, and library staffing reorganisation, according to Weiner (2009) and Zetterlund (2016) describe R&D as an organization's improvement and usage of new ideas or procedures for new system services. Libraries require new innovations to identify new services and a strong organisational culture for quality improvement and relevance in today's society.

Cultural differences affect organisational mental and social health (Baird et al., 2018). Communication, learning, change aversion, and skill and information exchange are affected by culture. Culture represents ML employees' beliefs. History, services, R&D, procedure, people monitoring, top management style, library mission, vision, standards, working environment, trust, and belief affect them. In ML civilizations, BDAR interactions are substantial. Environmental readiness-BDAR hypothesis:

H3a: Operational acceptance contributes to BDAR.
H3b: Culture contributes to BDAR.
H3c: Talents contribute to BDAR.

2.6.4 Acquisition Intention to Adopt Big Data Analytics in Malaysian Libraries

The following hypothesis presents the relationship between libraries' willingness to use BDA and the data creation activities that occur in MLs. This hypothesis is based on the statements obtained from the previous literature review as well as on the data creation activities that occur in MLs. We have come up with the following hypothesis:

H4: Acquisition intention significantly affects BDA adoption.

3.0 Research Methodology

The testing variables must be calculated to validate the study hypothesis. Develop the survey instrument and have academic experts evaluate it for qualitative analysis. Quantitative research validates theoretical frameworks using statistical analysis. This study collected data using a specific method and analysed it using structural equation modelling and partial least squares. The schematic in Figure 3 shows this study's thorough research strategy.

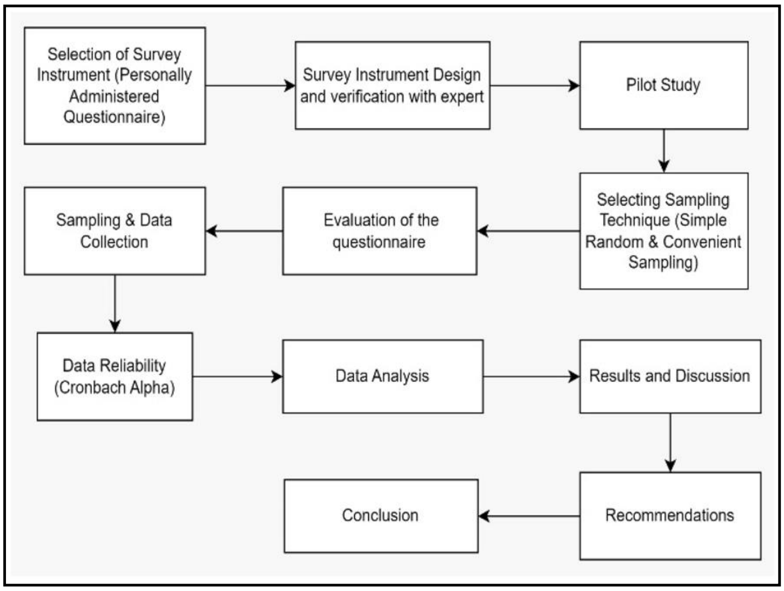

Figure 3: Adopted Research Flowchart

3.1 Pilot Test

This study's pilot included 34 Malaysian librarians, include chief librarians, and seniors. Participants evaluated the instrument's data collection and comprehension. Before the experiment, this evaluation assessed the questionnaire's applicability for Malaysian libraries and identified flaws and potential for improvement.

3.2 Measurement Items

The study on the BDA readiness on Malaysian libraries was taken using a simple method called "probability sampling" The measurement of the items used a 7-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = sometimes disagree, 4 = not sure, 5 = sometimes agree, 6 = agree, 7 = strongly agree). The objective of this research objective of this research is:

i) To determine the TOE for BDAR in Malaysian Libraries.
Ii) To identify the level of BDAR of Malaysian Libraries.
iii) To determine the effect of TOE on BDAR in Malaysian libraries.
iv) To determine the effect of BDAR on the acquisition intention of BDA.

4.0 Data Analysis and Results

The instruments for this research is divided into 6 sections: (a) demographic profile, (b) technology factors, (c) organization factors, (d) environment factor, (e) big data analytics readiness as the independent variables (IV) and (f) acquisition intention to adopt big data analytics as dependent variables (DV). The sections results of earlier exploration in Table 1:

Constructs	Mean	Standard Deviation	T-Statistics
ICT Infrastructure	0.091	0.046	1.968
Security	0.137	0.042	3.293
Data Scalability	0.132	0.046	2.869
Reliability	0.174	0.035	4.901
Management Support	0.011	0.054	0.203
Magnitude	0.162	0.059	2.748
Budgeting	0.005	0.038	0.123
Operational Acceptance	0.019	0.04	0.525
Culture	0.323	0.047	6.802
Talents	0.107	0.043	2.504
Big Data Analytics Readiness	0.471	0.044	10.595
Acquisition Intention to Adopt BDA	0.362	0.039	9.319

Table 1: Descriptive Analysis of the Study

4.1 Initial Analysis

The model measured internal consistency and indication reliability (factor loading). SEM-SmartPLS checked stability. Ramayah et al. (2018) measure data internal consistency with Cronbach's alpha and composite reliability. Taber (2018) accepts 0.7 Cronbach's. A construct dependability of 0.7 or greater is acceptable (Ramayah et al., 2018; Taber, 2018). For dependability, Ramayah et al. (2018) recommended indicator loading of 0.708 or above. If high-scoring items reinforce AVE and CR, loading >0.7 (Hair et al., 2017), 06 and 0.5 (Byrne, 2010), and 0.4 (Ziyae, 2016) are sufficient.

Previous SmartPLS research recommends convergent and discriminant validity analysis of statistical data (Gefen & Straub, 2005). Convergent validity (AVE) assures constructs have comparable measurements (Hair et al., 2017). The indicators should compare construct convergence to others. Convergent validity requires AVE > 0.50. Hair et al., (2017) and Ramayah et al. (2018) suggest deleting the reflecting indication when outer loading is <0.4 and retaining it when >0.70.

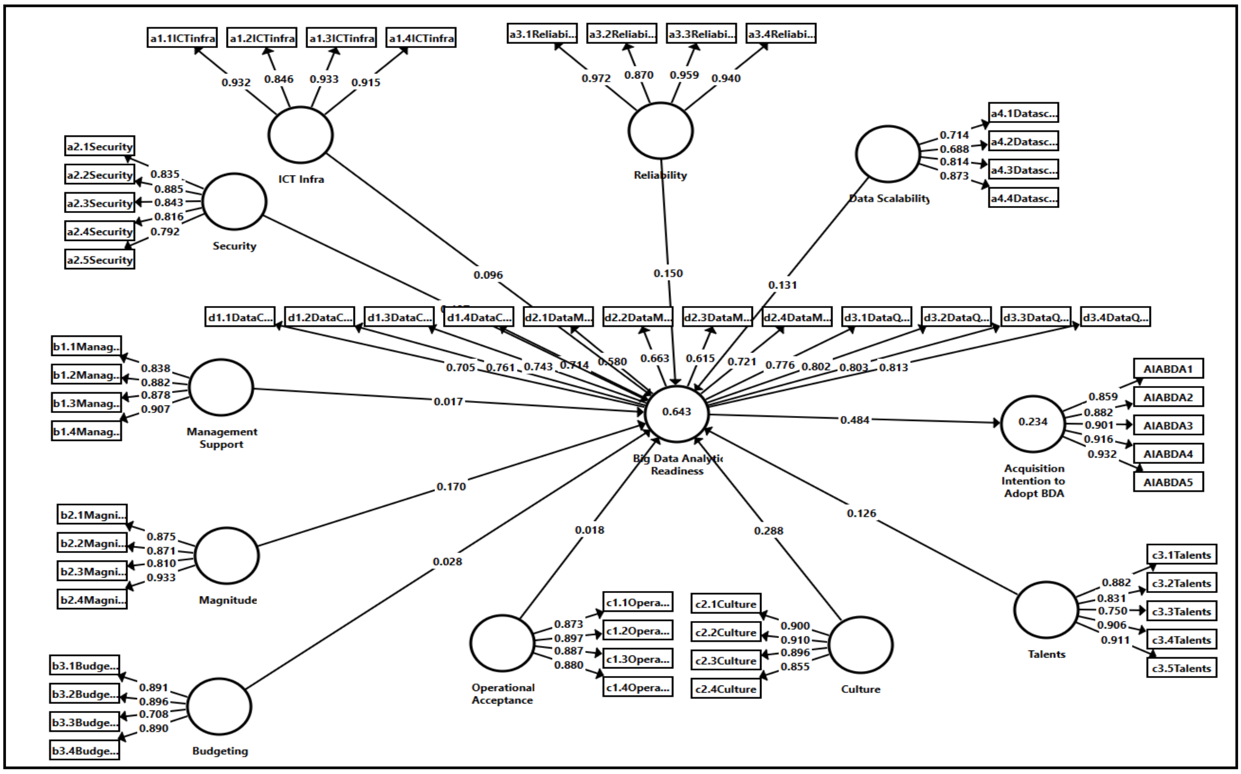

Figure 4: Initial Measurement of the Model by Items

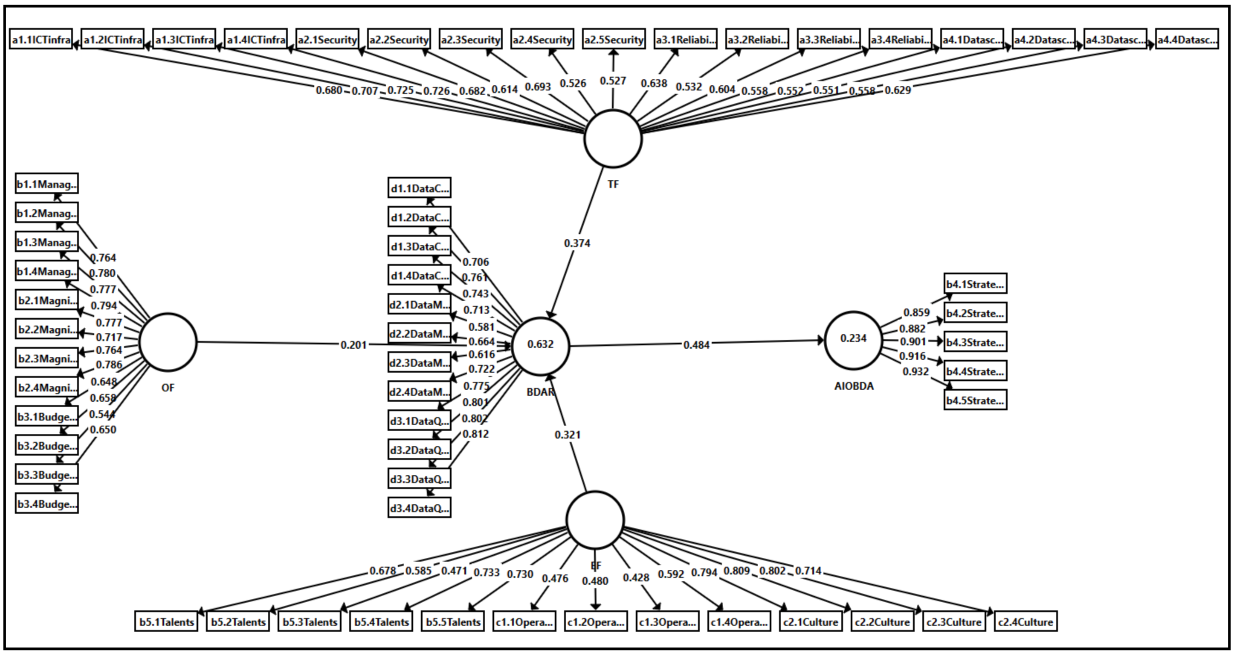

Figure 5: Initial Measurement of the Model by Construct

Table 2: Construct Reliability and Validity Analysis

Construct	Indicators		1st Run				2nd Run			
			Factor Loading	Cronbach's Alpha	Composite Reliability	AVE	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Technology Factors	ICT Infrastructure	a1.1ICT	0.932	0.928	0.949	0.823	0.933	0.928	0.949	0.824
		a1.2ICT	0.846				0.839			
		a1.3ICT	0.933				0.936			
		a1.4ICT	0.915				0.918			
	Security	a2.1Sec	0.835	0.892	0.920	0.697	0.836	0.892	0.920	0.697
		a2.2Sec	0.885				0.881			
		a2.3Sec	0.843				0.846			
		a2.4Sec	0.816				0.819			
		a2.5Sec	0.792				0.789			
	Reliability	a3.1Rel	0.972	0.953	0.966	0.877	0.972	0.953	0.966	0.877
		a3.2Rel	0.870				0.868			
		a3.3Rel	0.959				0.960			
		a3.4Rel	0.940				0.941			
	Data Scalability	a4.1Sca	0.714	0.776	0.857	0.602	0.724	0.776	0.857	0.603
		a4.2Sca	0.688				-			
		a4.3Sca	0.814				0.821			
		a4.4Sca	0.873				0.874			
Organization Factors	Management Support	b1.1Man	0.838	0.899	0.932	0.769	0.839	0.899	0.930	0.769
		b1.2Man	0.882				0.883			
		b1.3Man	0.878				0.877			
		b1.4Man	0.907				0.906			
	Magnitude	b2.1Mag	0.875	0.895	0.928	0.763	0.877	0.895	0.928	0.763
		b2.2Mag	0.871				0.871			
		b2.3Mag	0.810				0.808			
		b2.4Mag	0.933				0.933			
	Budgeting	b3.1Bud	0.891	0.868	0.912	0.723	0.894	0.868	0.912	0.723
		b3.2Bud	0.896				0.898			
		b3.3Bud	0.708				0.701			
		b3.4Bud	0.890				0.897			
	Operational Acceptance	c1.1Ope	0.873	0.909	0.936	0.935	0.877	0.909	0.935	0.782
		c1.2Ope	0.897				0.894			
		c1.3Ope	0.887				0.887			
		c1.4Ope	0.880				0.879			
	Culture	c2.1Cul	0.900	0.913	0.939	0.793	0.902	0.913	0.939	0.793
		c2.2Cul	0.910				0.909			
		c2.3Cul	0.896				0.895			
		c2.4Cul	0.855				0.856			
	Talents	c3.1Tal	0.882	0.911	0.933	0.737	0.881	0.911	0.933	0.736
		c3.2Tal	0.831				0.832			

		c3.3Tal	0.750				0.747			
		c3.4Tal	0.906				0.907			
		c3.5Tal	0.911				0.913			
Big Data Analytics Readiness (BDAR)	Data Collection	d1.1DCol	0.706	0.922	0.945	0.811	0.723	0.922	0.945	0.811
		d1.2DCol	0.761				0.789			
		d1.3DCol	0.743				0.763			
		d1.4DCol	0.714				0.729			
	Data Management	d2.1DMan	0.580	0.923	0.946	0.813	-	-	-	-
		d2.2DMan	0.663				-			
		d2.3DMan	0.615				-			
		d2.4DMan	0.712				-			
	Data Quality	d3.1DQua	0.776	0.939	0.957	0.847	0.822	0.939	0.957	0.847
		d3.2DQua	0.802				0.845			
		d3.3DQua	0.803				0.844			
		d3.4DQua	0.812				0.839			
Acquisition Intention to Adopt BDA		IABDA1	0.859	0.940	0.954	0.807	0.858	0.940	0.954	0.807
		IABDA2	0.882				0.879			
		IABDA3	0.901				0.899			
		IABDA4	0.916				0.918			
		IABDA5	0.932				0.934			

4.2 Convergent Validity

In this research, composite reliability (AVE) scores for all contracts exceed 0.50. It appears that the measurement has sufficient convergent validity. Table 2 assesses research convergent validity. The study found factor loading between 0.765 and 0.970 for each component. This study found AVE values from 0.602 to 0.877.

Table 3: Assessment of Convergent Validity

Constructs	Indicators	Factor Loading	Average Variance Extract (AVE)
Technological Factors			
ICT Infrastructure	a1.1ICT	0.933	0.824
	a1.2ICT	0.839	
	a1.3ICT	0.936	
	a1.4ICT	0.918	
Security	a2.1Sec	0.836	0.697
	a2.2Sec	0.881	
	a2.3Sec	0.846	
	a2.4Sec	0.819	
	a2.5Sec	0.789	
Reliability	a3.1Rel	0.970	0.877
	a3.2Rel	0.875	
	a3.3Rel	0.957	
	a3.4Rel	0.941	
Data Scalability	a4.1Sca	0.724	0.603
	a4.3Sca	0.821	
	a4.4Sca	0.874	
Organizational Factors			
Management Support	b1.1Man	0.839	0.769
	b1.2Man	0.883	
	b1.3Man	0.877	
	b1.4Man	0.906	
Magnitude	b2.1Mag	0.877	0.763
	b2.2Mag	0.871	
	b2.3Mag	0.808	
	b2.4Mag	0.933	

Budgeting	b3.1Bud	0.894	0.723
	b3.2Bud	0.898	
	b3.3Bud	0.701	
	b3.4Bud	0.897	
Environmental Factors			
Operational Acceptance	c1.1Ope	0.877	0.782
	c1.2Ope	0.894	
	c1.3Ope	0.887	
	c1.4Ope	0.879	
Culture	c2.1Cul	0.902	0.793
	c2.2Cul	0.909	
	c2.3Cul	0.895	
	c2.4Cul	0.856	
Talents	c3.1Tal	0.881	0.736
	c3.2Tal	0.832	
	c3.3Tal	0.747	
	c3.4Tal	0.907	
	c3.5Tal	0.913	
Big Data Analytic Readiness (BDAR)			
Data Collection	d1.1DCol	0.898	0.811
	d1.2DCol	0.895	
	d1.3DCol	0.917	
	d1.4DCol	0.892	
Data Quality	d3.1DQua	0.914	0.847
	d3.2DQua	0.925	
	d3.3DQua	0.941	
	d3.4DQua	0.900	
Acquisition Intention to Adopt BDA			
Acquisition Intention to Adopt BDA	b4.1Stra	0.858	0.807
	b4.2Stra	0.879	
	b4.3Stra	0.899	
	b4.4Stra	0.918	
	b4.5Stra	0.934	

Fornel and Lacker (1981) yield discriminant results in this investigation. See Fornell-Lackers criterion results in Table 4. Despite meeting the Fornell-Lackers criterion, the researcher performed HTMT analysis..

Table 4: Results of Fornell-Larcker Criterion

BDAR	**0.796**										
Budgeting	0.434	**0.850**									
Culture	0.683	0.438	**0.891**								
Data Scalability	0.607	0.484	0.504	**0.776**							
ICT Infrastructure	0.565	0.340	0.526	0.412	**0.908**						
Intention to Adopt BDA	0.471	0.339	0.417	0.454	0.316	**0.898**					
Magnitude	0.631	0.476	0.510	0.657	0.568	0.432	**0.873**				
Management Support	0.639	0.516	0.681	0.642	0.559	0.419	0.652	**0.877**			
Reliability	0.452	0.205	0.328	0.298	0.370	0.223	0.274	0.323	**0.936**		
Security	0.522	0.318	0.402	0.475	0.425	0.248	0.524	0.460	0.200	**0.835**	
Talents	0.482	0.330	0.426	0.462	0.271	0.389	0.379	0.463	0.227	0.323	**0.858**

In this investigation, HTMT is enough. This study's HTMT results are in Table 5. HTMT should be below 0.85 or 0.90 (Kline, 2016). HTMT values for this study are below value. This removes discriminant validity issues.

Table 5: Heterotrait-Monotrait Ratio (HTMT)

BDAR					
Budgeting	**0.472**				
Culture	0.731	**0.494**			
Data Scalability	0.710	0.590	**0.605**		
ICT Infra	0.597	0.373	0.569	**0.485**	
Intention to Adopt BDA	0.496	0.380	0.449	0.533	**0.334**

Magnitude	0.685	0.540	0.562	0.788	0.617	**0.471**				
Management Support	0.691	0.587	0.750	0.774	0.608	0.460	**0.727**			
Reliability	0.464	0.221	0.345	0.342	0.394	0.229	0.289	**0.344**		
Security	0.568	0.347	0.436	0.554	0.455	0.275	0.568	0.500	**0.206**	
Talents	0.497	0.365	0.446	0.539	0.276	0.405	0.413	0.501	0.232	**0.330**

We bootstrapped HTMT investigations to confirm the first. Ramayah et al. (2018) advised two-tailed tests with a 0.10 significance criterion for HTMT bootstrapping. Corrected confidence interval biases. Finding gives 1 5.0%–95.0% confidence. Discriminant validity is shown. See Table 6 for bias-corrected confidence intervals.

Table 6: Bias Corrected Confidence Interval

The Construct	Original Sample (O)	Sample Mean (M)	Bias	5.0%	95.0%
BDAR -> Acquisition Intention to Adopt BDA	0.471	0.474	0.003	0.381	0.550
Budgeting -> BDAR	0.005	0.007	0.002	-0.057	0.064
Culture -> BDAR	0.323	0.328	0.005	0.229	0.399
Data Scalability -> BDAR	0.132	0.133	0.001	0.057	0.207
ICT Infra -> BDAR	0.091	0.091	0.000	0.022	0.161
Magnitude_ -> BDAR	0.162	0.156	-0.007	0.073	0.259
Management Support -> BDAR	0.011	0.010	-0.001	-0.074	0.095
Reliability -> BDAR	0.174	0.173	-0.001	0.122	0.238
Security -> BDAR	0.137	0.142	0.005	0.065	0.206
Talents -> BDAR	0.107	0.102	-0.005	0.045	0.177

4.3 Assessing the Significance & Relevance of the Structural Model Relationship

Hair et al. (2014) suggest 500 subsamples. Table 7 shows structural model path coefficients. Study t=5.081–27.498. A high correlation exists (t-value > 1.645). According to Ramayah et al. (2018), the null hypothesis was significant (p-value < 0.05). Hair et al. (2017) suggest a p-value <0.05 for one- or two-tailed tests. Each construct in this study had 0.000 p-values.

Table 7: Path Coefficient of the Structural Model

The Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-values	p-values
Budgeting -> BDAR	0.005	0.005	0.038	0.123	**0.451**
Culture -> BDAR	0.323	0.323	0.047	6.802	0.000
Data Scalability -> BDAR	0.132	0.132	0.046	2.869	0.002
ICT Infra -> BDAR	0.091	0.091	0.046	1.968	0.025
Magnitude_ -> BDAR	0.162	0.162	0.059	2.748	0.003
Management Support -> BDAR	0.011	0.011	0.054	0.203	**0.419**
Operational Acceptance --> BDAR	0.021	0.019	0.040	0.525	**0.600**
Reliability -> BDAR	0.174	0.174	0.035	4.901	0.000
Security -> BDAR	0.137	0.137	0.042	3.293	0.001
Talents -> BDAR	0.107	0.107	0.043	2.504	0.006
BDAR --> Acquisition Intention to Adopt BDA	0.359	0.362	0.039	9.319	0.000

Although confidence interval bias is high, T-value and p-value support the path coefficient's importance. Ramayah et al. (2018) say dissertations need more than T- and p-values. Results (5.0%–95.0%) do not overlap in this study. The link matters (Ramayah et al., 2018). This study's bias and confidence interval are in Table 8.

Table 8: Bias Corrected Confidence Interval

The Relationship	Original Sample (O)	Sample Mean (M)	Bias	5.0%	95.0%
Budgeting -> BDAR	0.005	0.009	0.004	-0.063	0.066
Culture -> BDAR	0.323	0.322	-0.001	0.248	0.401
Data Scalability -> BDAR	0.132	0.132	0.000	0.047	0.194
ICT Infra -> BDAR	0.091	0.090	-0.001	0.023	0.169
Magnitude_ -> BDAR	0.162	0.163	0.001	0.071	0.268
Management Support -> BDAR	0.011	0.010	-0.001	-0.073	0.106
Operational Acceptance -> BDAR	0.021	0.019	-0.002	-0.056	0.098
Reliability -> BDAR	0.174	0.175	0.002	0.109	0.226
Security -> BDAR	0.137	0.135	-0.002	0.068	0.207

Talents -> BDAR	0.107	0.110	0.002	0.025	0.169
BDAR --> Intention to Adopt BDA	0.359	0.362	0.003	0.282	0.434

5.0 Discussion Strategic Factors of BDAR in Malaysian Libraries

The basic link led the researcher to seek BDAR-level dimensions. The thorough mapping review found the key BDAR dimensions. Numerous factors go into dimension selection. Dimensions should match ML data process. The researcher removed one data scalability and one data management item from the study.

5.1 Technology Factors

Explaining BDA readiness approach. Technical capacities to adapt and use BDA determine ML preparedness, according to TF. Zhan & Widén (2019) show how technology changes libraries. Previous studies addressed TF readiness. BDA-related tasks, data activities, and features are examined. BDA-ML technology alignment will be evaluated. MLs plan technological infrastructure, data security, dependability, and scalability based on BDA acceptance and use TF preparedness. Also included are BDA uptake and usage TF readiness findings. MLs faced problems and worked and consumed data differently. Thus, the researched MLs may have varied BDA TF assessment adoption levels.

Library science professionals highlight technology for BDA preparation in banking, education, health care, public sector, business, etc. Gabel & Tokarski (2014), Kalema & Mokgadi (2017), Motau (2016), Motau & Kalema (2016), Rani (2016), Al-Barashdi & Al-Karousi (2019), Davenport & Dyché (2013) and Showers (2014). Technical and organisational BDA adoption factors have been studied. Technology success requires ICT infrastructure, security, stability, and data scalability. The questionnaire determined MLs' BDA readiness library technology capability factor. Modern library technology may enhance data utilisation, claimed Showers (2014). The analysis averaged 4.67. Pimentel (2019) found 4.32-5.14 a good mean score indicator. This proves ML and BDA are compatible. All libraries digitised, according to Chen et al. (2015) and Osman (2018). MLs' annual tech updates demonstrate this.

Every technological progress required ICT infrastructure. The numerous sectors have automated and roboticized to reduce human error and boost output. Libraries and information science also need modern ICT infrastructure including servers, networks, and storage to meet online service demand. Library services and daily work depend on online transactions. Wang et al. (2016) suggest libraries and technology are interdependent. MLs also budget for ICT updates, maintenance, hardware, and software annually. Certain MLs oversee the intuition's ICT infrastructure purchases and upgrades. MLs always value library ICT infrastructure.

5.2 Organization Factors

Management support, funding, and size all affect the organization's readiness. A corporation needs a large data collection to produce terabyte or petabyte amounts of data (Sanaei, 2014). Huge libraries rarely have trouble generating large amounts of data. Many large companies utilise BDA to track market growth, client demand, and product sales. Libraries are classified as public, academic, or special. Each category has a specific purpose. Each library has a different collection and services. According to Wang et al. (2016), libraries generate one petabyte of data per year from online transactions, purchases, and other services.

Kiconco (2018) found that “the management of the Makerere University Library utilises data for the construction of sustainable collections.” According to Kim & Cooke (2017), “the public libraries in South Korea aim for collection development demand and service planning based on both borrowing and admission data.” Even though only a tiny fraction of MLs have fully adopted BDA, management support is crucial to its success since it affects project budget planning. Management must grasp BDA's role in library management to avoid mistakes while making decisions.

BDA in libraries requires lots of data. Borrowing, return, visit, procurement, user, and service data are available from the library. Library magnitude includes collection size, user population, online services, acquisition efforts, etc. The library generates terabytes or petabytes of data regularly and annually. Data creation from online and manual transactions promotes libraries to analyse each employment activity.

Most businesses budget annually. HR, salaries, training, system development, sales, marketing, maintenance, and other management topics are discussed. Annual ML activities include purchasing, subscriptions, system maintenance, project planning, programming, etc. According to Perpustakaan Negara Malaysia (2017), “we already allocate a specific budget for each branch in every state to have an equal development and to support all the activities.” The government gave Perpustakaan Negara Malaysia RM72.2 million in 2020 to buy more e-books and online databases for online learning due to the COVID-19 pandemic (Perpustakaan Negara Malaysia, 2021). The OF factor alignment assessment for BDA adoption shows good preparedness..

5.3 Environment Factors

To meet customers' changing needs, companies must embrace change (Lalic & Marjanovic, 2017). The development of change inside an organisation must also have the skills and talents to implement changes in the workplace. MLs aim to provide workers with many opportunities to improve their skills in library science and technology (Li et al., 2017).

Environment for library BDA adoption is closely linked to talent development and the need to improve user service. Previous study by Campbell & Cowan (2016), Gamage (2016), Rajasekar (2014) and Simović (2018) supports this claim. The earlier researcher highlighted culture, abilities, and operational acceptance. The sub-dimension hypothesis was denied, hence the researcher had to stop this study. However, the future researcher must study operational acceptance in greater detail.

Numerous studies explained the institution's culture. Culture is when employees adopt something new that needs major modifications to their regular routines. ML labour was mostly cataloguing, buying, and other routine activities. Culture promotes norms, methods, missions, and objectives for project completion years. BDA in MLs may require cultural consideration.

Sharing, workshops, and other techniques can teach human traits and skill. MLs provide well-planned technological education, but analytical training is insufficient. Job obligations force some ML librarians to learn analytics on their own. Library training eventually covered these skills as they grew more relevant. BDA must highlight talent throughout its operations to flourish.

MLs' biggest asset is talent, and BDA success depends on leveraging it. Many skilled staff help MLs score well. MLs may need a clear BDA strategy ready for full execution to reap the benefits of data values that produce correct decision-making outputs. However, BDA's function and benefits may have been unclear, making implementation difficult. This is false since financing and library type affect BDA efficacy.

From this perspective, MLs are mature but underutilised by employees. ML top management may also lack BDA understanding. All MLs will lose BDA acceptance and implementation. Environment factor requirements include good evaluation score and ready %. We simply need a few cultural modifications to succeed with the BDA initiative.

Even data-intensive libraries have a middling BDA adoption and implementation rating. MLs' substantial data use in operations and services may improve their BDA capabilities. Again, the association is clear, but it may influence ML BDA use.

5.4 Hypothesis Discussion

This study has eleven hypotheses. Eight hypotheses were supported and three were not. Both managerial support and budgeting theories about organisation elements were unsupported. Operational acceptability, an environment factor hypothesis, was also rejected. These three dimensions help libraries use big data analysis, even though they are not hypotheses. This claim is supported by numerous studies, including Al-Barashdi & Al-Karousi (2019), Karno (2022), McLeod et al. (2017), Motau & Kalema (2016), Olendorf & Wang (2018) and Romijn (2014).

Working organisations must consider budget. Most firms budget for annual operations. HR, salaries, training, system development, sales, marketing, maintenance, and other management issues are covered. Budget preparation is normally handled by library upper management. This involves training, technology updates, and administrative oversight. Budgeting for all library operations affects this study's results. Despite being disproven, the budget theory is crucial to this large-scale data analysis project. MLs' annual activities include purchasing, subscriptions, system maintenance, project planning, programming, etc. According to Perpustakaan Negara Malaysia (2021), "we already allocate a specific budget for each branch in every state to have an equal development and to support all the activities include technology upgrading and etc."

Study denies management support. Each company endeavour requires senior management endorsement. Big data analysis is poorly understood by top management, and Malaysian libraries rarely use it. Most libraries measure performance via descriptive, shallow data analysis. Top management must comprehend the big data project before a work process can work, according to Karno (2022). Big data analysis was first challenging to integrate into our library management system. It's now crucial to our plan.

The last hypothesis rejected was operational acceptance. Klievink et al., (2017), Motau & Kalema (2016) and Romijn (2014), found that operational acceptability impacts big data analysis. Operations acceptance hypothesis is not supported by this study. Senior management gives lower-level workers commands in Malaysian libraries. These instructions are assumed to be completed and evaluated by each division or section. It considerably impacts the study's results. Future library science and information management scholars should study the aforementioned constraints, as many studies in other domains stress the importance of these three criteria in project success.

6.0 Conclusion

This section encompasses the authors' last remarks, the study's limitation, theoretical contributions, and practical contributions.

6.1 Theoretical Contribution

This research establishes an empirical foundation for MLS BDAR determination. Previous investigations failed to support an empirical framework for this topic. Our conceptual framework was based on Al-Barashdi & Al-Karousi (2019), Klievink et al. (2017) and Romijn (2014) theories and models. The model used MAMPU (2018), Motau & Kalema (2016), and Tornatzky et al. (1990). The preliminary studies help the researcher conceptualise the framework's initial dimension. This study also gives significant data and credible sources to strengthen the framework.

The proposed conceptual framework considers dimension and BDAR in MLs. TOE was used in this experiment. Subdimensions included ICT infrastructure, security, dependability, data scalability, management support, size budgeting, strategies, and skills. BDAR for MLs focuses on data collection, management, and quality.

Accordingly, the study revealed that BDAR is significantly related to and aligned with AITABDA in MLs. BDAR and AITABDA are closely connected in MLs, the study found. The study also found that TOE factors boost ML BDAR. TF sub-dimensions including ICT infrastructure, data security, reliability, and scalability affect BDAR success, this study found. TF is now assessed in ML BDAR. The OF sub-dimensions management support, magnitude, and budget were taken from previous research. The relationship is unique in MLs BDAR research and considerably enhances assessment and implementation. Many disciplines have explored LE—culture and skills. This study benefits from relationships. The study expanded TOE literature by adding readiness concept sub-dimensions to the ML BDA readiness framework. The mediator BDAR dimension quantified ML alignment for BDA use and considerably improved ML BDA acceptance. Otherwise, library science BDAR literature is limited. A validated framework will spread the notion to MLs..

6.2 Practical Contribution

This work created a complete ML BDAR assessment tool. The survey was for this study. From the conceptual framework, the study created a questionnaire. Making a good dimension-measuring device required many processes. Several professionals checked it. The instrument was pilot-tested for Cronbach's Alpha in each dimension. Data imply the tool fits the study. Multiple academic and conference articles validated the tool. Thus, the questionnaire is essential for measuring TF, OF, EF, and BDAR in other studies.

The instrument can be utilised in all Malaysian and international libraries, although this study concentrates on ML librarians. School libraries and resource centres can use the proposed device. Archives, record centres, and other information specialists can use it. System, TF, and BDAR surveys can match data activity and method.

To determine dimension components, another study can use or substitute questionnaire items. The device may simplify BDAR measurement and assessment. Integrating ML BDAR into the organisation system allows monitoring. The company can evaluate system readiness using ICT infrastructure, security, and size. The questionnaire may digitally examine MLs' TF, OF, and BDAR to align BDA adoption. The programme speeds project readiness evaluations and system development.

6.3 Research Limitations & Future Research

This study measures ML BDAR. The literature search only covers BDA, library data, and tech readiness. Data was lacking for library decision-making and performance monitoring. Questionnaire used for organisational evaluation. Finding relevant BDAR literature for Library Science and Information Management is the study's main challenge. BDAR literature is limited. No model or theory exists in the field. An empirically unsupported aspect of this study.

For BDAR, this study assessed library readiness and environment. The framework overlooked operating acceptability (staff needs, high impact, library competitiveness and advancement) and culture (policies, procedures, clear vision, job activity performance). As ML BDA cannot use dimension. A study classifies MLs by location, local economy, primary organisation policies, finances, and more. Operatorally, the researcher cannot generalise the study's phenomenon. BDA and library operational acceptance and culture might be studied.

The second limitation is responder classifications and sample size. This study largely involves ML librarians. Many academic, public, special, government, and commercial libraries exist. Numbering job scope and activities simplifies manual analysis. This inquiry involved several libraries. Not all MLs are user-friendly. Before starting, the researcher had to describe the study's purpose. Many librarians refused the survey. Future research can solve these issues by adding responders and school libraries, industrial resource centres, and similar MLs. Archivists, curators, and knowledge hubs can respond. The framework may need minor changes for selected respondents' BDAR. Comparing libraries or qualitatively assessing BDAR study importance may require more investigation. Responses can exceed this study's. Understanding the situation may require more respondents than the sample size.

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