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Article

Exploring the factors influencing the adoption of business intelligence in Malaysia's service sector

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Abstract: In the realm of contemporary business, Business Intelligence (BI) offers significant potential for informed decision-making, particularly among executives. However, despite its global popularity, BI adoption in Malaysia's service sector remains relatively low, even in the face of extensive data generation. This study explores the factors influencing BI adoption in this sector, employing the Technology Acceptance Model (TAM) as its conceptual framework. Drawing on relevant BI literature, the study identifies key TAM factors that impact BI adoption. Using SEM modelling, it analyses quantitative data collected from 45 individuals in managerial roles within Malaysia's service sector, particularly in the Klang Valley. The findings highlight the crucial role of Perceived Usefulness in influencing the Behavioral Intention to adopt BI, serving as a mediating factor between Computer Self-efficacy and BI adoption. In contrast, Perceived Ease of Use does not have a direct impact on BI adoption and does not mediate the relationship between Computer Self-efficacy and Behavioral Intention. These insights demonstrate the complex nature of BI adoption, emphasizing the importance of Perceived Usefulness in shaping Behavioral Intentions. The outcomes of the study aim to guide executives in Malaysia's service sector, outlining key considerations for successful BI adoption.

Keywords: business intelligence; TAM; computer self-efficacy; perceived usefulness; perceived ease of use; behavioral intentions

1. Introduction

In today's rapidly evolving business landscape, characterized by globalization and technological innovation, the integration of information technology (IT) is essential for economic growth and organizational success (Albelbisi et al., 2021). Business Intelligence (BI) systems, which emerged in the 1990s, play a key role in collecting, analyzing, and disseminating data to facilitate informed decision-making (Mohammad et al., 2022). The BI market has experienced exponential growth, driven by the adoption of cloud services and advanced data analytics technologies (Gottfried et al., 2021). Organizations worldwide are making significant investments in BI and analytics to enhance decision-making processes and achieve improved outcomes. However, despite its importance, BI adoption faces numerous challenges, with over 70% of planned outcomes remaining unachieved (Salisu et al., 2021). Understanding the key success factors is crucial for overcoming these challenges and ensuring the effective adoption of BI systems, particularly in the service sector.

Malaysia's service sector holds a prominent position, contributing approximately 56% to the country's GDP (Department of Statistics Malaysia, 2021) and serving as a significant source of employment. The Malaysian government actively promotes the growth of this sector through various initiatives and policies aimed at attracting foreign investment and enhancing global competitiveness (Mohd Shukri and Harun, 2021). Key areas within Malaysia's service sector include finance, transportation, logistics and storage, and information and communication technology (ICT).

The country has made substantial investments in digital infrastructure, positioning itself as an attractive destination for companies seeking to establish a presence in Southeast Asia's rapidly expanding digital economy. In recent years, Malaysia's service sector has experienced significant growth, with businesses increasingly adopting digital technologies to remain competitive (EPU, 2021). The imperative for technology adoption has become even more pronounced with the emergence of new markets and the widespread availability of digital technologies. The COVID-19 pandemic has revealed the disparities between organizations that successfully integrate digital technology into their operations and those that lag behind, demonstrating the importance of technology adoption for organizations seeking to respond to shifting market demands (Mohsin et al., 2022). In sectors such as banking, financial services, and insurance (BFSI), technology has been a driving force, enabling institutions to innovate and streamline operations through digital technologies like blockchain, artificial intelligence, and machine learning (Feyen et al., 2021). The ICT industry, encompassing telecommunications, software development, and computer networking, remains at the forefront of technological innovation, driven by emerging technologies like 5G, cloud computing, and the Internet of Things (IoT) (Ya'akub, 2020).

BI has emerged as a critical technology for the service sector, facilitating data analysis and providing actionable insights that drive informed decision-making (Jourdan and Massey, 2016). Evidence suggests that implementation of BI improves performance, productivity, and efficiency across various dimensions of enterprise development, resource management, vendor-buyer relationships, and cost savings (Tavera et al., 2021). Prominent global companies, including American Express, Expedia, Coca-Cola, Netflix, Starbucks, and Walmart, leverage BI to optimize operations and identify cost-saving opportunities (Morris, 2021).

Despite the growing importance of BI, its adoption within Malaysia's service sector remains relatively low, presenting a challenge in an increasingly competitive and rapidly evolving business environment (Ahmad and Hossain, 2018). Reports indicate that only a small percentage of organizations in this sector have implemented BI tools, which may limit their capacity to make informed decisions and maintain a competitive edge (EY, 2020; MIDA, 2019, 2021; MDEC, 2020). Overall technology adoption in the service sector is approximately 20%, emphasizing the urgent need for digital transformation (Bernama, 2020). The COVID-19 pandemic has further accentuated this necessity, with surveys indicating that a shortage of technology talent and a lack of technical understanding are significant barriers to adoption (CPA Australia, 2021).

Given the low adoption rate of BI in Malaysia's service sector, this study aims to investigate the factors influencing the Behavioral Intention to adopt BI. To achieve this objective, the research will utilize a model grounded in the Technology Acceptance Model (TAM) framework, which is widely recognized for its effectiveness in explaining the factors that drive BI adoption at the organizational level.

However, this study will focus specifically on individual users. The primary research question guiding this study is: *What factors influence the adoption of BI in* Malaysia's service sector*?*

This study contributes to the existing body of BI literature by identifying the key factors that drive BI adoption within the context of Malaysia's service sector. Furthermore, it aims to offer valuable guidance to executives in this sector, facilitating the efficient implementation of BI and enhancing the likelihood of successful outcomes.

This paper is structured as follows: Section 2 presents a literature review, Section 3 outlines the methodology used in the analysis, Section 4 discusses the research results, and Section 5 provides concluding remarks.

2. Literature review

2.1. Business intelligence (BI)

The definition of the term 'Business Intelligence' (BI) has been a subject of debate among various authors. Dresner (as cited by Kumar et al., 2024) first defined the term in 1989. Despite conflicting historical accounts, the core definition of BI has remained consistent. According to Maliki and Toute (2024), BI entails a range of strategies and tools designed to capture and transform raw data into valuable insights for business analysis. Ranjan and Foropon (2021) further describe BI as a multifaceted system that integrates organizational, technological, and strategic components. In contemporary contexts, BI is increasingly powered by artificial intelligence (AI), enabling non-technical users, including corporate executives, to model, analyze, explore, exchange, and organize data (Kronz et al., 2022). This technological landscape includes data mining, data warehousing, online analytical processing, organizational reporting, and enterprise performance management, all of which work together to transform organizational data into actionable insights (Phan and Teoh, 2024). The accessibility of BI has fundamentally transformed how organizations conduct their operations. Effectively deploying BI technology has become a critical asset, allowing organizations to gain a competitive edge by obtaining deeper insights into customers, markets, and operations (Buhasho et al., 2021).

Due to the numerous benefits associated with BI, an increasing number of organizations are adopting these systems. For example, Alkhwaldi (2024) examined the user acceptance behavior of BI systems within a healthcare setting, while Jiménez-Partearroyo et al. (2024) explored the role of BI in the tourism industry. Additionally, Abdulnabi (2024) focused on BI adoption among SMEs in Iraq. However, as previously mentioned, there is a lack of research on BI adoption within the services sector as a whole.

2.2. BI Adoption

A search of the SCOPUS database using the keywords 'business intelligence' and 'adoption' for articles published between 2020 and 2024 yielded 13 relevant articles after filtering for English language publications, the subject areas of business, management and accounting, and articles from specific source titles (Appendix A).

These articles were subsequently analyzed. Most of the articles focused on BI adoption while a few examined the impact of BI adoption (Bhatiasevi and Naglis, 2023; Martins et al., 2024).

In terms of research approaches, the literature revealed various methodologies. Some studies employed quantitative methods (Abdulnabi, 2024; Subramaniam et, al., 2024) while others utilized qualitative approaches (Martins et al., 2024; Wee et al., 2024). Additionally, Andar and Kasparova (2024) and Gaol et al. (2020) adopted case study approaches. The search also revealed that the studies predominantly concentrated on either organizational factors (Bhatiasevi and Naglis, 2020; Hmoud et al., 2023; Qatawneh, 2024) or individual factors, specifically focusing on employees (Abdulnabi, 2024; Jaradat et al., 2024).

Furthermore, it is important to note that different authors employed various theoretical frameworks to study BI adoption. Among the theories used were the Technology Acceptance Model (TAM) (Abdulnabi, 2024), the Diffusion of Innovation (DOI) model (Jaradat et al., 2024), and the Technology, Organization, and Environment (TOE) framework (Hmoud et al., 2023; Qatawneh, 2024; Subramaniam et al., 2024). In addition to these three models, Chi and Mahmud (2020), Malki and Touate (2024) and Salisu et al. (2021) noted that previous studies have also used the Unified Theory of Acceptance and Use of Technology (UTAUT) model and the Delone and McLean models.

This study adopts the TAM as the framework for examining BI adoption, as it is the most widely employed research model in this area. Chi et al. (2020) conducted a systematic literature review of BI adoption and found that 15 out of 44 articles adapted TAM. TAM serves as a theoretical framework designed to elucidate and predict individuals' acceptance and use of technology. Originally formulated by Fred Davis in the 1980s (Abdulnabi, 2024), TAM has undergone several iterations to enhance its explanatory power and practical relevance (Bhattarai and Maharjan, 2020). TAM is instrumental in predicting IT adoption and elucidating the factors that influence it, comprising four components: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Usage (Behavioral Intention to Use), and Actual System Use (Marikyan and Papagiannidis, 2023). While this study adopts these components, it excludes the Actual System Use component. Given that actual BI usage levels in Malaysia remain relatively low, particularly in the services sector, this study replaces Actual System Use with Intention to Use.

The role of Intention to Use, a psychological factor, is crucial in determining individuals' engagement with technology (Basuki et al., 2022). This intention reflects a predisposition toward using specific technologies and encompasses individuals' commitment and inclination to adopt particular technologies or perform specific behaviors. A positive Intention to Use indicates a higher likelihood of actual usage and active participation (Bhattarai and Maharjan, 2020; Dewanti and Sabri, 2022; Kamal et al., 2022; Ni, 2020).

Given that this study focuses on individuals, human factors were considered in the analysis of BI adoption. According to Malki and Touate (2024), who reviewed literature from 2012 to 2022, several human factors influence BI adoption. The two most significant factors identified were PU and PEOU, aligning with the decision to adopt the TAM for this study. These constructs fundamentally shape an individual's usage behavior (Ain et al., 2019). In addition, Malki and Touate (2024) highlighted managerial factors, such as managerial skills and resourcefulness, as well as individual traits, including educational levels, interpersonal skills and self-efficacy (SE). This study includes SE, particularly computer SE, as a factor influencing BI adoption, as individuals' belief in their ability to achieve desired outcomes can directly motivate their behavioral intention (Yu, 2022). Several studies, including those by Almulla (2021), Dewanti and Sabri (2022), Kamal et al. (2022) and Lavidas et al. (2023) have incorporated SE as a significant factor influencing BI adoption (Appendix B).

A conceptual framework has been developed based on the literature review. This framework (**Figure 1**) integrates key findings from studies conducted by Abdulnabi (2024), Almulla (2021), Bhattarai and Maharjan (2020), Chaveesuk and Chaiyasoonthorn (2022), Dewanti and Sabri (2022), Kamal et al. (2022), Yu (2022), among others.

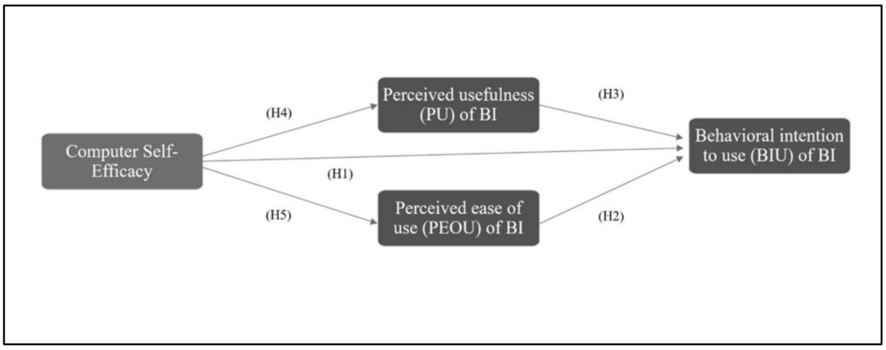

Figure 1. Conceptual framework.

2.3. Development of hypotheses

2.3.1. Self-efficacy (SE) and BI

SE is defined as an individual's belief in their ability to achieve desired outcomes, serving as an external factor that influences perceptions of technological competence (Bandura, cited by Kamal, 2022). High levels of SE are associated with positive attitudes and intentions toward technology adoption (Dewanti, 2022). Incorporating self-efficacy into the analysis enhances the understanding of the factors influencing technology acceptance, particularly the impact of individuals' beliefs in their technological capabilities (Pan, 2020). Computer SE, a concept closely related to general SE, specifically refers to an individual's belief in their ability to effectively use computers and related tools (Yu, 2022). Positive experiences and successful interactions with technology can enhance computer SE, while negative experiences or lack of familiarity can diminish it (Almulla, 2021).

Building on insights garnered from previous research, particularly the studies conducted by Dewanti and Sabri (2022) and Yu (2022), a consistent trend of positive relationships has been identified. However, it is important to note that statistical significance has not been universally established in these studies. Thus, Hypothesis 1 (H1) is formulated to underscore the importance of individuals' confidence in their computer skills and to highlight the need for a detailed exploration of this relationship within the specific context of Malaysia's service sector.

H1. There is a significant positive relationship between computer self-efficacy and the Behavioral Intention to Use BI in Malaysia's service sector.

2.3.2. Perceived ease of use (PEOU) and BI

PEOU reflects an individual's subjective assessment of how straightforward and user-friendly a specific type of technology is (Davis, as cited by Bhattarai and Maharjan, 2020). Previous research on this relationship has yielded mixed results, introducing an element of complexity to this hypothesis. Notably, studies such as Abdulnabi (2024) have reported a significant positive correlation between PEOU and Behavioral Intention to Use, suggesting that a perception of ease of use may indeed influence the inclination to adopt BI. These mixed findings underscore the complex nature of the relationship and highlight the need for further exploration within the specific context of Malaysia's service sector. Validating Hypothesis 2 (H2) would offer valuable insights into the role of PEOU in shaping the Behavioral Intention to Use BI systems in this dynamic professional setting.

H2. There is a significant positive relationship between Perceived Ease of Use and the Behavioral Intention to Use BI in the service sector in Malaysia.

2.3.3. Perceived usefulness (PU) and BI

PU refers to an individual's belief that using a specific system will enhance their work performance, including dimensions like effectiveness, productivity, and time savings (Davis, as cited by Kamal et al., 2022). PU is associated with the ability to achieve desired outcomes with accuracy, completing tasks efficiently, and optimizing time management. Collectively, these dimensions measure the overall value that a system contributes to an individual's work.

PU encompasses an individual's subjective assessment of the extent to which a technology, such as BI, contributes to enhancing job performance and effectiveness. Studies by Bhattarai and Maharjan (2020) and Yu (2022) have demonstrated a positive relationship between PU and Behavioral Intention to Use BI. These findings underscore the critical role that perceived utility plays in shaping individuals' intentions to adopt BI systems within the unique context of Malaysia's service sector. Confirming Hypothesis 3 (H3) would further validate the strength of this relationship and offer practical insights for promoting the effective adoption of BI tools in professional settings.

H3. There is a significant positive relationship between Perceived Usefulness and Behavioral Intention to Use BI in Malaysia's service sector.

2.3.4. PEOU and PU as mediating variable between SE and BI

PEOU and PU exert a direct influence on the intention to use technology (as described above) and also mediate the relationship between Intention to Use and SE (Chen and Aklikokou, 2020). In their study examining Thai students' intention to use cloud classrooms, Chaveesuk and Chaiyasoonthorn (2022) conducted a mediation analysis that revealed both PU and PEOU as mediators in the relationship between computer SE and the intention to use cloud classrooms. Similar hypotheses have been consistently supported by Bhattarai and Maharjan (2020), Kamal et al. (2022) and Yu (2022).

However, the role of PEOU and PU as mediators in the relationship between computer SE and BI adoption remains underexplored in previous BI studies (see Appendix A and B). Addressing this gap could provide valuable insights into the specific mechanisms that influence BI adoption in Malaysia's service sector. Understanding these mechanisms is crucial for shaping attitudes and intentions toward the incorporation of BI into work practices.

Validating Hypotheses 4 (H4) and 5 (H5 would enhance the understanding of these key relationships and offer practical implications for promoting BI adoption in professional settings, emphasizing the need for further investigation within the context of the service sector.

H4: Perceived Usefulness mediates the relationship between computer self-efficacy and the Behavioral Intention to use BI in Malaysia's service sector.

H5. Perceived Ease of Use mediates the relationship between computer self-efficacy and the Behavioral Intention to use BI in Malaysia's service sector.

3. Research methodology

This study adopted a positivist research approach and utilized an online survey questionnaire, administered in English through Google Forms, to collect data. The research methodology applied in this paper is structural equation modelling (SEM), with all measurements taken using a 5-point Likert scale. The research design adopted an explanatory approach, aiming to provide insights into the reasons behind specific phenomena (Hasa, 2021). The questionnaire was divided into two sections: the first section captured demographic information, while the second section explored factors influencing the adoption of BI, specifically Perceived Usefulness, Perceived Ease of Use, and Computer Self-efficacy, along with Behavioral Intention to Use BI systems. The items for all constructs were adapted from Chaveesuk and Chaiyasoonthorn (2022), as their framework was found to be similar to this research area. Moreover, they have included items from previous studies, which was also reviewed.

The study employed a cross-sectional design (Kesmodel, 2018) and utilized a quantitative data collection approach through a questionnaire distributed via professional networking platforms, social media, and among colleagues and adult students. The study focused on professionals in the service sector within Malaysia's Klang Valley region, specifically targeting those in the banking, financial services, and insurance (BFSI), ICT, and transportation, logistics, and storage industries. Participants were required to have a minimum of two years of experience working in micro, small, medium and large enterprises. While the target was to reach 200 respondents, only 45 participants were obtained after one month through convenience and snowball sampling methods.

The study population comprised individuals in various management roles within Malaysia's service sector. Respondents, representing different levels of management, were asked to evaluate their awareness of the concept of BI after it was explained to them. The validity and reliability of the questionnaire were assessed using measures such as Cronbach's Alpha, Composite Reliability, exploratory factor analysis, and Average Variance Extracted (Bhattarai and Maharjan, 2020; Dewanti and Sabri, 2022; Hasa, 2021; Kesmodel, 2018).

4. Results and discussion

An analysis of respondents' demographics, as depicted in **Table 1**, revealed that 11% identified as Gen Z (ages 18 to 26), 64% as Gen Y (ages 27 to 42), 22% as Gen X (ages 43 to 58), and only 2% as Baby Boomers (ages 59 to 77). The majority of respondents were from the Gen Y category, indicating a significant representation in the study. In terms of gender, male respondents comprised 56% of participants, while female respondents constituted 44%, reflecting a slightly higher participation rate among males. The generational breakdown illustrates the age distribution, highlighting the predominant presence of Gen Y respondents, which aligns with their likely prominence in the workforce. The gender distribution indicates a slight imbalance in participation, with a higher representation of males, suggesting a need for further exploration into gender dynamics in BI adoption.

Table 1. Respondents' demographics analysis.

Category	Items	Frequency	Percentage%
Gender	Male	25	56
	Female	20	44
Age	18–26 (Gen Z)	5	11
	27–42 (Gen Y)	29	64
	43–58 (Gen X)	10	22
	59–77 (Baby Boomers)	1	2
Education	High School Certificate (SPM)	1	2
	Diploma	4	9
	Degree	25	56
	Masters	13	29
	Doctorate	2	4
Job Level	Associate/Junior Executive	5	11
	Coordinator/Analyst/Specialist	8	18
	Team Leader/Supervisor/Asst. Manager	8	18
	Manager/Lead Manager/Senior Manager/Project Manager	16	36
	Associate Director/Director/Senior Director	5	11
	C–level/President/VP/Executive Director	3	7
Company Size	Less than 5 (Micro Enterprise)	7	16
	5–19 (Small Enterprise)	3	7
	20–49 (Medium Enterprise)	7	16
	More than 50 (Large Enterprises)	28	62
Industry	Banking, Financial Services, and Insurance	18	40
	Information and Communication Technology (ICT)	14	31
	Transportation, Logistics and Storage	13	29

Participants in the study exhibited diverse educational backgrounds: 2% held a high school certificate (SPM), 9% possessed a diploma, 56% held a bachelor's degree, 29% had a master's degree, and 4% had a doctorate. This diverse educational profile reflects a broad spectrum of knowledge and skills within the sample, enriching the research with varied perspectives and experiences.

The analysis of job levels revealed a varied representation, including 11% in Associate/Junior Executive roles, 18% as Coordinators/Analysts/Specialists, 18% as Team Leaders/Supervisors/Assistant Managers, 36% as Managers/Lead

Managers/Senior Managers/Project Managers, 11% as Associate Directors/Directors/Senior Directors, and 7% in C-level positions (President/VP/Executive Directors).

The distribution by company size revealed that 62% of respondents were from large enterprises, indicating a dominant presence of BI adoption in this category. The breakdown of respondents included 16% from micro enterprises (<5 employees), 7% from small enterprises (5–19 employees), 16% from medium enterprises (20–49 employees), and 62% from large enterprises (>50 employees). The study included respondents from three selected industries within the service sector: 40% from BFSI, 31% from ICT, and 29% from transportation, logistics, and storage.

Table 2 presents a comprehensive analysis of Computer SE, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention to Use (BITU). Participants exhibited notable levels of Computer SE, with mean scores ranging from 3.978 to 4.467, indicating moderate agreement (small standard deviations, SE: 0.108 to 0.151). The positive kurtosis suggests a deviation from normal distribution, while the negative skewness indicates higher ratings of Computer SE.

Table 2. Descriptive statistics.

Variable	Item	Mean	Std. Dev	Std Error	Kurtosis	Skewness
Computer Self-Efficacy	SE1	4.467	0.726	0.108	1.817	−1.370
	SE2	4.311	0.848	0.126	0.670	−1.127
	SE3	3.978	1.011	0.151	0.506	−0.921
	SE4	4.311	0.848	0.126	1.650	−1.361
	SE5	4.222	0.823	0.123	−0.395	−0.698
Perceived Usefulness	PU1	4.489	0.661	0.099	−0.181	−0.944
	PU2	4.378	0.716	0.107	1.381	−1.101
	PU3	4.467	0.726	0.108	1.817	−1.370
	PU4	4.356	0.802	0.120	5.656	−1.853
	PU5	4.444	0.755	0.113	1.274	−1.293
Perceived Ease of Use	PEOU1	3.844	1.021	0.152	−0.076	−0.612
	PEOU2	3.756	1.004	0.150	−0.145	−0.467
	PEOU3	4.089	0.949	0.142	−0.103	−0.851
	PEOU4	3.489	1.160	0.173	−0.102	−0.703
	PEOU5	3.778	1.085	0.162	0.210	−0.764
Behavioral Intention To Use	BITU1	4.133	0.842	0.126	0.026	−0.740
	BITU2	4.200	0.726	0.108	−1.006	−0.328
	BITU3	4.089	0.733	0.109	0.198	−0.503
	BITU4	4.133	0.726	0.108	−1.031	−0.210
	BITU5	3.933	0.889	0.133	−0.454	−0.474

Perceived Usefulness emerged as a critical factor for BI adoption, with mean scores ranging from 4.356 to 4.489. The standard deviations indicate variability, while the standard error values (0.099 to 0.120) indicate precise estimates. The kurtosis values vary, and the negative skewness implies a distribution that favors higher ratings of Perceived Usefulness. In contrast, the mean scores for Perceived Ease of Use range from 3.489 to 4.089. The higher standard deviations (indicating moderate precision, with standard error values ranging from 0.142 to 0.173) and negative kurtosis and skewness suggest a trend toward higher ratings.

Behavioral Intention to Use, a predictor of BI adoption, has mean scores between 3.933 and 4.200. The standard deviations indicate variability, and the standard error values (0.108 to 0.133) suggest precise estimates. The varying kurtosis and negative skewness indicate a preference for higher intentions to use BI.

The kurtosis and skewness values presented in **Table 2** support these trends, demonstrating participants' inclination toward higher ratings. The measurement model analysis, informed by previous studies (Kamal et al., 2022; Yu, 2022), assesses validity and reliability through convergent validity, internal consistency, and overall reliability.

The measurement model evaluation, depicted in **Table 3**, examined factor loadings for Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention to Use (BITU), and Computer Self-Efficacy (SE). The factor loadings for PU, PEOU, and BITU exceeded the recommended threshold of 0.7, confirming robust convergent validity. However, within the SE construct, item SE2 fell below this threshold, indicating the need for further investigation into its impact on the overall model.

Table 3. Factor loading.

Variable	Item	FL
Computer Self-Efficacy	SE1	0.927
	SE2	0.668
	SE3	0.81
	SE4	0.882
	SE5	0.758
Perceived Usefulness	PU1	0.84
	PU2	0.727
	PU3	0.871
	PU4	0.744
	PU5	0.862
Perceived Ease of Use	PEOU1	0.868
	PEOU2	0.896
	PEOU3	0.765
	PEOU4	0.899
	PEOU5	0.923
Behavioral Intention to Use	BITU1	0.893
	BITU2	0.871
	BITU3	0.875
	BITU4	0.805
	BITU5	0.836

Table 4 presents three key parameters: Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Composite Reliability (CR). The high CA scores (SE: 0.862, PU: 0.866, PEOU: 0.921, BITU: 0.907) indicate strong internal consistency among the constructs. AVE scores exceeding 50% confirm that the constructs effectively explain their respective variances. Additionally, the consistently high CR scores (SE: 0.907, PU: 0.905, PEOU: 0.940, BITU: 0.932) further affirm the reliability and internal consistency of each construct, all of which meet the recommended thresholds.

Table 4. Cronbach's alpha (CA), average variance extracted (AVE), and composite reliability (CR).

Variable	CA	AVE	CR
Computer Self-Efficacy	0.862	0.663	0.907
Perceived Usefulness	0.866	0.658	0.905
Perceived Ease of Use	0.921	0.760	0.940
Behavioral Intention to Use	0.907	0.734	0.932

The findings from the hypothesis testing, summarized in **Table 5** and presented in **Figure 2**, contribute to the understanding of the complex relationships between the variables. Hypotheses 1 and 2, which proposed relationships between Computer Self-efficacy (SE) and Behavioral Intention to Use (BITU), as well as between Perceived Ease of Use (PEOU) and BITU, respectively, were rejected due to a lack of statistical significance. In contrast, Hypothesis 3, which posited a significant positive relationship between Perceived Usefulness (PU) and BITU, was supported. Furthermore, the mediating role of Perceived Usefulness in the relationship between Computer Self-efficacy (SE) and BITU (Hypothesis 4) was confirmed. However, the mediating role of Perceived Ease of Use was not found to be statistically significant (Hypothesis 5).

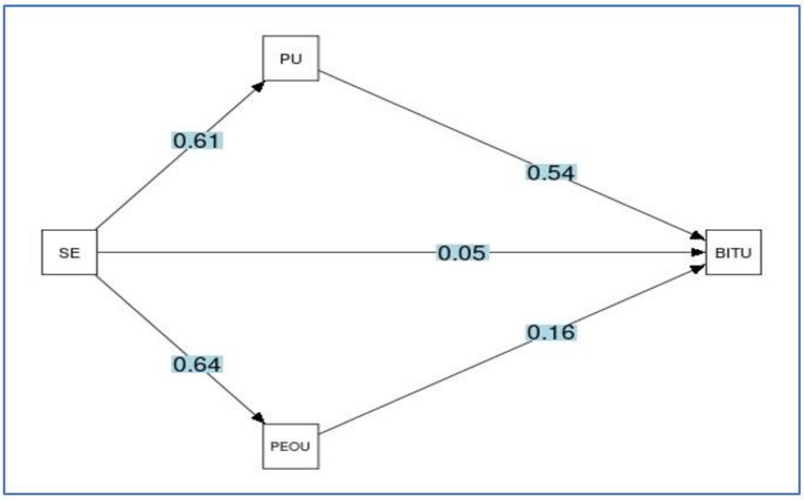

Figure 2. Standardized path coefficients.

Table 5. Hypothesis testing.

Hypothesis	Path	Est.	Std. Err.	*z*-value	*p*-value	Std lvl	Std All	Results
H1	SE → BITU	0.05	0.16	0.28	0.78	0.05	0.05	Not Supported
H2	PEOU → BITU	0.12	0.11	1.09	0.28	0.12	0.16	Not Supported
H3	PU → BITU	0.61	0.16	3.84	0.00	0.61	0.54	Supported
H4	SE → PU → BITU	0.32	0.10	3.07	0.00	0.32	0.33	Supported
H5	SE → PEOU → BITU	0.10	0.09	1.07	0.29	0.10	0.10	Not Supported

In the context of this study, two out of the five previous investigations examined the direct relationship between Computer Self-Efficacy and Behavioral Intention to Use. Dewanti and Sabri (2022) found a positive relationship that was statistically insignificant, while Yu (2022) reported a statistically significant positive relationship. Notably, the exploration of the relationship between Computer Self-Efficacy and Behavioral Intention to Use within the framework of BI Adoption is unprecedented in prior studies.

The lack of statistical significance in the association between Perceived Ease of Use and Behavioral Intention to Use suggests that this connection may not be applicable in the broader context of Malaysia's service industry. This finding aligns with results from technology adoption studies by Bhattarai and Maharjan (2020) and Dewanti and Sabri (2022). However, a study by Kikawa et al. (2019), which focused on BI adoption using the TAM, yielded distinct results, highlighting the complexity and context-dependency of technology adoption in the specific domain of BI.

The substantial standardized path coefficient in Hypothesis 3 indicates that Perceived Usefulness significantly influences the Behavioral Intention to Use BI in the Malaysian service sector. The statistical significance of this relationship emphasizes that individuals who perceive BI as useful are more likely to intend to use it. While this finding aligns with previous studies, the divergent results in Kikawa et al. (2019) underscore the complexity of BI adoption, suggesting a need for further investigation into the specific factors influencing adoption in various contexts.

Hypothesis 4 reveals that the standardized path coefficient indicates that Perceived Usefulness significantly mediates the relationship between Computer Self-efficacy and Behavioral Intention to Use BI. This suggests that higher levels of Computer Self-efficacy lead individuals to perceive BI as useful, subsequently increasing their intention to use it. This finding is consistent with studies conducted by Almulla (2021) and Yu (2022). Notably, the mediating role of PU in the relationship between BITU and BI has not been explored in previous studies, highlighting the novel contributions of the current research to the existing literature.

In Hypothesis 5, while the standardized path coefficient suggests a positive mediating effect of Perceived Ease of Use, the lack of statistical significance indicates that this mediating relationship may not be applicable in the broader context of the Malaysian service sector. This finding contrasts with results from other technology adoption studies, implying that additional factors may exert a more substantial influence on the relationship between Computer Self-efficacy and Behavioral Intention to use BI. The mediating role of Perceived Ease of Use in the relationship between Computer Self-efficacy and Behavioral Intention to use BI has not been previously examined, emphasizing the need for further research to explore the specific dynamics and factors that affect BI adoption.

In summary, the study's findings indicate that the direct relationships between Computer Self-Efficacy and Perceived Ease of Use with Behavioral Intention to Use BI were not statistically significant. However, Perceived Usefulness emerged as a significant predictor of Behavioral Intention to Use BI and served as a mediating factor linking Computer Self-efficacy and Behavioral Intention to Use in BI. The lack of statistical significance regarding the mediating role of Perceived Ease of Use suggests that contextual variations may influence this relationship. These results underscore the complex nature of BI adoption and highlight the need for further research to gain a comprehensive understanding of the factors influencing BI adoption in Malaysia's service sector.

5. Conclusion

This study investigated factors influencing BI adoption in Malaysia's service sector, with a particular focus on potential mediating factors. The findings revealed that both Computer Self-efficacy and Perceived Ease of Use did not demonstrate significant direct relationships with Behavioral Intention to use BI. In contrast, Perceived Usefulness emerged as a significant predictor and a confirmed mediating factor in the relationship between Computer Self-efficacy and Behavioral Intention to Use BI, while Perceived Ease of Use did not serve as a mediator. These findings underscore the crucial role of Perceived Usefulness in shaping Behavioral Intention to Use BI and highlight its influence on the relationship between Computer Self-efficacy and BI adoption.

Importantly, this research addresses gaps in the existing literature by exploring the relationship between Computer Self-efficacy and Behavioral Intention to Use BI in the context of BI adoption. It also provides new insights by examining the mediating role of Perceived Usefulness and Perceived Ease of Use in the relationship between Behavioral Intention to use BI and actual BI adoption, thereby enhancing our understanding of the dynamics and factors influencing successful BI adoption in the service sector.

However, the study cautions against generalizing its findings to other industries or countries due to the unique characteristics of the service sector. The sample, drawn from personal and professional contacts, may lack diversity in industry representation. Additionally, the cross-sectional design limits the ability to establish causal relationships, and the reliance on self-reported measures of Computer Self-efficacy introduces potential bias. Furthermore, important mediating factors such as attitudes toward technology and organizational support were not examined, and variables like technological readiness, perceived risk, and organizational culture were overlooked. Future research should incorporate a broader range of mediating factors to achieve a more comprehensive understanding of the dynamics of BI adoption. (Almulla, 2021; Bhattarai and Maharjan, 2020; Dewanti and Sabri, 2022; Kamal et al., 2022; Kikawa et al., 2019; Yu, 2022).

This study makes a significant contribution to the theoretical understanding of BI adoption in the service sector. The non-significant direct relationships between

Computer Self-efficacy and Perceived Ease of Use with Behavioral Intention to Use BI highlight the need to explore additional influential factors. Conversely, the positive relationship between Perceived Usefulness and Behavioral Intention to Use underscores the critical importance of users' perceptions regarding the utility of BI. The confirmed mediating role of Perceived Usefulness in the relationship between Computer Self-efficacy and Behavioral Intention to Use emphasizes the complex interplay of factors that shape adoption decisions (Dewanti and Sabri, 2022; Kamal et al., 2022; Kikawa et al., 2019).

From a practical perspective, organizations and policymakers in Malaysia's service sector should prioritize enhancing the Perceived Usefulness of BI systems to drive adoption. The finding of non-significant direct relationships suggests that a broader focus is needed, extending beyond training or ease of use. Strengthening users' computer self-efficacy through tailored training programs, while simultaneously emphasizing the practical benefits, emerges as a powerful strategy. Additionally developing customized BI implementation strategies that consider user characteristics and perceptions is essential for optimizing adoption initiatives, improving decision-making processes, and enhancing overall competitiveness.

Despite its limitations, this study offers valuable insights into the factors influencing BI adoption in Malaysia's service sector. Future research should aim to address these limitations by exploring diverse contexts, employing longitudinal designs, and investigating additional influencing and mediating factors. Strengthening the validity of findings will be crucial to informing organizational decisions related to successful BI technology adoption.

For future research, conducting a comparative study across sectors and countries could help identify contextual factors that influence BI adoption behavior. Additionally, examining technology implementation strategies, understanding the drivers and barriers to continued BI usage, and exploring the impact of external factors on BI adoption would significantly enhance organizational strategies. Furthermore, integrating qualitative methods with quantitative data could provide deeper insights into users' attitudes and experiences with BI adoption.

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Appendix A

Table A1. Selected Scopus articles (2020–2024).

Author(s)	Year	Theory/Model/Study	Unit of Analysis
Abdulnabi S.M.	2024	TAM and Quality of Information, Organization Readiness and Technology Infrastructure,	owners, managers and information system staff in Iraqi SMEs
Andar J.; Kasparova P.	2024	Impact of Management Support on Business Intelligence Adoption	Case Study
Bhatiasevi V.; Naglis M.	2020	TOE & Balance Scorecard	SMEs in Thailand
Gaol F.L.; Abdillah L.; Matsuo T.	2020	Application of Business intelligence on Accounting System	Case Study
Hatamlah H.; Allahham M.; Abu-AlSondos I.A.; Al-junaidi A.; Al-Anati G.; Al-Shaikh A.M.	2023	Business intelligence as Mediator	Case study
Hmoud H.; Al-Adwan A.S.; Horani O.; Yaseen H.; Zoubi J.Z.A.	2023	TOE	individuals in various management roles within HEIs in Jordan
Jaradat Z.; Al-Dmour A.; Alshurafat H.; Al-Hazaima H.; Al Shbail M.O.	2024	DOI	Employees of Jordanian Insurance Companies
Jaradat Z.; AL-Hawamleh A.; Altarawneh M.; Hikal H.; Elfedawy A.	2024	Relationship between Intellectual Capital (Human, Structural, Relational), business intelligence technologies, and the decision to innovate	company & financial managers, heads of accounting departments, and IT department staff of companies listed in Amman Stock Exchange,
Joshua S.R.; Mogea T.	2020	Adoption framework using Agile Analytics	Case study
Martins A.; Bianchi de Aguiar M.T.; Sambento M.; Branco M.C.	2024	integration of business intelligence systems in the digital transformation context and its impact on management control and organizational performance	Qualitative
Nithya N.; Kiruthika R.	2021	Impact of Business Intelligence Adoption on Performance on banks	Conceptual Framework
Qatawneh N.	2024	TOE	Employees Working for Jordanian Commercial Banks
Subramaniam R.; Palakeel P.; Arunmozhi M.; Sridharan M.; Marimuthu U.	2024	OCKTUEES, TOE	employees within an enterprise environment
Wee M.; Scheepers H.; Tian X.	2023	Role of leadership on BI adoption	Case studies SME Owners
Zoubi M.A.L.; Alfaris Y.; Fraihat B.; Otoum A.; Nawasreh M.; Alfandi A.	2023	DOI & Project Management Maturity	Jordanian Companies with more than 40 workers

Appendix B

Table B1. Selected google scholar articles (2020–2023).

Author(s)	Year	Independent Variable (IV)	Mediator	Models	Sector
Nazri, & Iskandar	2021	Infrastructure, Knowledge Process, Human Capital, Culture, Application	-	Resource-Based View Theory (RBV), BI Maturity Model	Education
Bhattarai, & Maharjan,	2020	Social Influence, Accessibility, Computer Self Efficacy, Infrastructure, Enjoyment	PEOU, PU, Attitude towards Use	Technology Acceptance Model (TAM2),	Education
Ahmad et al.	2020	Sustainability, Competitive Pressure, Market Trends, Compatibility, Technology Maturity, Leadership, Commitment and Support, Satisfaction with Existing Systems, Sustainable Data Quality and Integrity, Users' Traits, Interpersonal Communications	-	Technology-Organizational-Environment (TOE)	Textile and apparel
Kamal et al.	2022	Experience, Subjective Norms, Self-Efficacy	PEOU, PU	Technology acceptance model (TAM2),	Manufacturing
Dewanti, & Sabri	2022	Satisfaction, Self-Efficacy, Performance Expectancy, Effort Expectancy, Social Influence, PU, PEOU, Perceived Behavioral Control, Attitude Toward Using		UTAUT, TPB and TAM2.	Education
Yu.	2022	Computer Self-Efficacy, Construction of Foreign Language Intelligence	PEOU, PU	TAM2	Education
Almulla	2021	Computer self-efficacy (CSE), Subjective Norm, Perceived Enjoyment	PEOU, PU, Attitude towards Use	TAM2	Education
Lavidas et al.	2023	Subjective Norm, Perceived Self-Efficacy (PSE), Technology Complexity (TC).	PEOU, PU	TAM2	Education