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Big Data Analytics to Support Open Innovation Strategies in Banks

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Abstract: Today's dynamic business environment has pushed service-oriented firms such as banks to collaborate with external partners through open innovation (OI) to address issues of service differentiation, optimize customer experience, and create effective open innovation strategies (OIS). However, the essential elements required to design OIS and the methods to manage these strategies are missing. Therefore, this study aims to investigate the strategic resources essential to creating OIS and identify the tools to manage these resources. Following the fundamentals of the resource-based view (RBV), bank openness (BOP), selection of external partners (SEP), open innovation methods (OIM), formalizing collaboration processes (FCP), and banks' internal practices (BIP) are identified as the strategic elements required for creating OIS, and the role of big data analytics (BDA) in these strategic resources is examined. The data were collected through a survey questionnaire from 425 bank executives employed at different digital banks located in Malaysia. To achieve our research objectives, a quantitative deductive research design was employed and the collected data were processed in WarPLS using the structural equation modeling (SEM) technique to test the research hypotheses of this study. The empirical results reveal that BDA has a significant positive impact on BOP, SEP, and FCP, whereas OIM and BIP have an insignificant positive impact. The findings of this study contribute to designing a robust digital strategy to enhance the banking sector's contribution to the development of financial industries in developing countries by employing BDA as a major strategic policy tool of OIS

Keywords: open innovation; big data analytics; strategic resources; digital strategy; financial sector

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1. Introduction

Innovation is a key to organizational success, growth, and the acquisition of strategic resources (Alassaf et al. 2020). Particularly, open innovation (OI) is essential to resolve complex organizational issues by suggesting the most relevant ideas, solutions, and people entirely from outside the organization (Chesbrough 2004). Through OI, organizations successfully acquire breakthrough ideas by connecting with a global pool of talented people, which allows them to develop innovative products and services, respond to dynamic workforce requirements, and find a solution to unresolved issues (Bigliardi et al. 2021). Progressive organizations have started to transcend their boundaries to improve their innovative activities through the conscious inflow and outflow of knowledge, which is helping them to embrace OI and optimize innovation performance (Chesbrough 2003; Naseer et al. 2021). Alternatively, acquiring revolutionary ideas and knowledge through external sources help organizations in reducing costs and investment in R&D as well as sharing risk with external partners (Elia et al. 2020; Leckel et al. 2020).

The concept of OI has received considerable attention from scholars and practitioners over the past two decades; however, a large cluster of studies have focused on investigating OI from a firm-level perspective (Antons et al. 2016; Bertello et al. 2022; Greco et al. 2021; Nestle et al. 2019; Radziwon and Bogers 2019; Sengupta and Sena 2020;

Shaikh and Randhawa 2022; Teplov et al. 2018; West and Bogers 2017). The findings of these studies have established that the management of OI hinges on firms' openness (Bogers et al. 2018a; Laursen and Salter 2006), the selection of external partners (Sofka and Grimpe 2010), OI methods (Veugelers and Cassiman 1999), formalizing collaboration processes (Vlaar et al. 2007), and internal practices (Lakemond et al. 2016). A few studies have also highlighted that firms in the past have used multiple OI models to successfully develop innovation strategies and accelerate innovation-based business activities which require external support, critical knowledge, and identifying innovative methods for acquiring and creating knowledge (Bogers et al. 2017; Gatzweiler et al. 2017; West and Bogers 2017; Zhu et al. 2019). This represents a disagreement in the literature about the barriers and drivers of OI which can be classified into cultural, legal, financial, and economic (Greco et al. 2019; Vanhaverbeke et al. 2017). The admitted complexities of the OI process and organizations' surge for innovative strategies demand logical, analytical, and technology-based solutions for the management of the OI process.

In this regard, big data (BD), through its analytical capabilities, has received particular attention as it has the potential to develop OI strategies (OIS) by managing the above factors (Bogers et al. 2019). Big data analytics (BDA), which is linked to the digital revolution, has profoundly reshaped organizations' learning processes and methods to achieve a competitive advantage in both the digital and physical worlds (Alberti-Alhtaybat et al. 2019; Chen and Zhang 2014; Hartmann et al. 2016; Lanzolla and Giudici 2017; Tian 2017). Digitalization has created new business avenues for organizations considering innovative business models in data-driven industries (Caputo et al. 2019; Rochet and Tirole 2006; Garzella et al. 2021) by improving interconnection between more than two customers, which may maximize their financial performance (Capurro et al. 2022; Erevelles et al. 2016; Saura 2021). The financial industry in general and banks in particular are the clearest examples of data-driven industries (Zillner et al. 2016). Banks can leverage BDA to streamline their OI processes by capturing customers' data for business transformation, generating new revenue streams, managing risks, and enhancing customer loyalty (Ali et al. 2021). However, streamlining BDA to develop OIS creates new challenges as the literature lacks a commonly accepted OI model that can be cloned to banks. Based on this argument, this study attempts to explore the role of BDA in creating OIS for banks. Specifically, we aim to investigate the following research questions:

1. What are the essential strategic resources required to create effective OIS for banks?
2. What is the role of BDA in creating and managing OIS for banks?

To answer these research questions and achieve the objectives of this study, banks were selected as a case study, which allow categorizing the strategic resources relevant to developing OIS as well as investigating the effect of BDA due to three main reasons. First, BDA features provide infrastructural resources to the banks which are used for knowledge creation, the control of organizational processes, and the diversification of products and services (OECD 2014). This is relevant to banks, especially for service differentiation, as customers often face difficulty in differentiating between different banks due to the heterogeneity of services (Ali 2018; Fasnacht 2018). Second, even though banks are known as the largest producer of BD, the banking industry is yet to fully harness it to design innovative products and services, enhance user experience, improve customer satisfaction, and achieve loyalty (Ali et al. 2021). Alternatively, it will allow banks to remedy the criticism of cloning user innovation models from non-bank firms (Gianiodis et al. 2014). Third, banks in the past have been criticized for poor portfolio and innovation management after the financial crisis in 2008 (Damanpour et al. 2009; Priem et al. 2011; Sirmon et al. 2007) and are likely to be exposed to similar crises triggered by the ongoing COVID-19 pandemic. Therefore, developing OI models using BDA will help the banks to adjust to the new normal after the COVID-19 pandemic, consolidate their strategic resources, and effectively manage Fintech to remain a step ahead of their competitors.

This study is expected to have several important contributions. First, this study will help in investigating the many aspects and discrete benefits of BDA in developing OIS, which will contribute to understanding the innovation concept by linking it to the banking industry (Bogers et al. 2017; West and Bogers 2017). Second, the banking industry is yet to fully benefit from OI like other large firms due to the lack of a commonly accepted model to create OI (Usman et al. 2018; Vanhaverbeke et al. 2017). The insight of this study will facilitate the regulators of banks to consider operationalizing the model discussed in this study as a benchmark and to design OIS to create a dynamic business ecosystem. Third, the extended discussion in this study on OI and BDA will offer a range of methods to bankers looking to develop OIS supported by scientific evidence and logical explanations powered by BDA, which will help banks in absorbing the Fintech revolution and integrating open banking in their operations.

Section 2 of this paper discusses the state of the art of BDA, its role in the creation of OIS, and our research hypotheses. The major methods and research techniques used for data collection and analysis are presented in Section 3. The main findings are presented in Section 4. Finally, Section 5 discusses major research findings and concludes this study with implications and limitations.

2. Literature Review

2.1. Background of OI

The invention of OI can be linked to the unconventional practices of large innovative firms deviating from traditional innovation methods (Chesbrough 2003, 2006). The pioneering study on OI defined it as "the flow of inbound or outbound ideas towards the organization and transferred to the market from inside or outside the organization" (Chesbrough 2003). The current definition of OI has been significantly modified by innovation scholars and Chesbrough to emphasize entities' surge for inflow and outflow of knowledge. Chesbrough (2006) recoined OI and asserted that organizations purposely use knowledge inflows and outflows for accelerating their internal innovation process and market expansion. Recent modifications in OI are associated with different business models practiced by progressive organizations and it can be defined as "purposive management of the inflows and outflows of knowledge across organizational boundaries to create a distributive innovation process using financial and non-financial methods in a way that it diverges with organizations existing business models" (Chesbrough and Bogers 2014). Precisely, OI can be described as a distributed innovation process resulting due to the deliberate flow of information across entire organizational hierarchies (Naseer et al. 2021).

A number of studies have explored multiple aspects of OI ranging from underlying issues to the requirement of experts and the nature of the project (Ahn et al. 2017; Du et al. 2014; Kim et al. 2015). A few studies have also focused on investigating the significance of organizational platforms, business ecosystems, and social issues in publicly administrated organizations (Ahn et al. 2019; Schmidthuber et al. 2019). Scholars argued that the successful capitalization of OI relies on establishing a flexible culture essential to restructuring current business models in a way that fosters OIS (Bogers et al. 2019). This highlights entities' need to integrate strategic and smart assets coupled with technologically driven internal and external sources aligning with their business models to power OI. The current era characterized by unprecedented changes demands organizations to resolve issues by extracting value from existing knowledge through modern architectures and systems instead of developing an entirely new piece of knowledge (Naqshbandi and Jasimuddin 2022). Despite the significance of integrating systems and architectures to gain real value from knowledge (Chesbrough 2006), there is no evidence in the extant literature about the strategic assets required to manage OI in organizations.

2.2. Operationalizing BDA in Banks

Data scientists defined BDA as "a unified approach rendered for the management, processing, and analysis of unstructured data to extract a meaningful insight for creating sustained value, optimizing performance, and achieving competitive advantage" (Wamba et al. 2017). Earlier studies on BDA described it as a 3Vs (volume, velocity, and variety) concept (Duan and Xiong 2015); later on, Wamba et al. (2015) recoined the term and characterized it as a 5Vs (volume, velocity, verity, veracity, and value) phenomenon. A categorical interpretation of the 5Vs highlighted that volume represents the daily creation of voluminous data from multiple sources at an exponential rate, velocity determines the prompt response to capture BD, variety represents multiple data sources (including new ones), veracity determines the reliability of data, and value means the extraction of economic benefits from available BD. Recently, a few studies (Mishra et al. 2017; Seddon and Currie 2017; Wamba and Mishra 2017) extended BD's dimensions and established that it should be described as a 7Vs (volume, velocity, verity, veracity, value, variability, and visualization) concept due to variations in the flow and sources of data (variability) and the importance of visualizing data by experts to prepare it for analysis (visualization).

BDA has become a top trend in academia and research in recent years and its analytical capabilities have convinced academicians and practitioners to position it at the forefront of future research agendas in the fields of business management and information systems (De Mauro et al. 2016; Gandomi and Haider 2015; Del Vecchio et al. 2018). The research in academia on BDA gained significant momentum after the hallmark study of McAfee et al. (2012), who regarded it as a major frontier of science, innovation, and the industrial revolution of the new millennium. BDA is categorized as large datasets originating from multiple sources at a high speed. BDA trends, applications, and growth started to take off in 2015, and a number of studies were conducted to analyze its impact on business, organizations, and many other domains of life (Del Vecchio et al. 2018).

A few recent studies have described BDA as a strategic component used for managing customer relations, operational risks, and overall operations of firms to maximize their financial performance (Bresciani et al. 2018; Germann et al. 2014; Kiron et al. 2013; Mikalef et al. 2019; Wamba et al. 2017). From a managerial perspective, BDA offers infinite data to streamline business processes, supply chains, and workforce performance, as well as to improve organizations' internal collaboration and analyze consumers' behavioral patterns (Bresciani et al. 2018; Dubey et al. 2019). Additionally, reports have argued that BDA helps in gaining a deeper insight into customers' preferences extending beyond the traditional methods of information collection, especially related to the latent needs of customers (Mora Cortez and Johnston 2017; Watson et al. 2018). Furthermore, organizations in the past have successfully implemented complex and voluminous data for strategic decision making, as well as scientifically supported and logically explained actions (Bertello et al. 2021; George et al. 2016; Mazzei and Noble 2017). Nonetheless, organizations concerned with developing new customer management strategies; creating innovative products, services, and business models; and enhancing customer experience, satisfaction, and loyalty are required to carefully manage millions of data sources (Levine et al. 2017; Mahmoud et al. 2018; Shipilov et al. 2017).

BDA and its significance in the financial industry are also widely debated in the literature as it is a frontier of future innovations (Hasan et al. 2020). Innovative financial services create large datasets daily through online peer-to-peer lending, crowdfunding, SME financing, assets, wealth, and trading, as well as mobile-payment-managing platforms, cryptocurrencies, and remittance administration channels. These datasets are used by financial analysts for strategic investment decisions to investigate consumers' spending behaviors for products and service customization (Hale and Lopez 2019). BDA has also contributed to improving different stakeholders' understanding of financial market trends, strategic decision making to enhance the quality and security of services, transparency, risk analysis, algorithm trading, and transformational culture (Ali et al. 2021; Diebold et al. 2019; Shen and Chen 2018). Table 1 outlines the chronological development of BDA together with some of its applications in the financial industry.

Table 1. Developments in BDA and its applications in the financial industry.

Event	Source	Explanation/Application
Introduction of BDA in research	(McAfee et al. 2012)	It was featured as a frontier of science, innovation, and the new-millennium industrial revolution.
Evolution of BDA as 3Vs	(Duan and Xiong 2015)	3Vs (volume, velocity, and verity) described BDA as voluminous data originating from multiple sources at a high speed.
Extension of BDA as 5Vs	(Wamba et al. 2015)	5Vs (volume, velocity, verity, veracity, and value) defined BDA as voluminous data originating from multiple sources from high-speed reliable networks, resulting in economic benefits.
Further extension of BDA as 7Vs	(Mishra et al. 2017; Seddon and Currie 2017; Wamba and Mishra 2017)	7Vs added two additional dimensions (variability and visualization) to the previous 5Vs which essentialized the significance of the difference in data flow and experts to visualize BDA to extract actual value.
BDA creation through innovative financial services such as online peer-to-peer lending, crowdfunding, SME financing, assets, wealth, trading, and mobile payment managing platforms, cryptocurrencies, and remittance administration channels	(Hale and Lopez 2019)	These sources are used by financial analysts to make strategic investment decisions, analyze consumers' spending patterns, and customize financial products and services.
BDA enhances understanding of financial markets	(Shen and Chen 2018)	This alternatively resulted in smart and careful investment decisions taken by the public.
Banks accessing trillions of data from various points	(James 2019)	Bankers use BDA to improve the quality and security of services.
Banks leveraging BDA to enhance their social and environmental performance	(Ali et al. 2021)	Bankers harness BDA to improve their environmental social and governance (ESG).

2.3. Operationalizing BDA in Banks

Almost all the features of BDA (7Vs) exceptionally fit into the fundamental requirements of OI outlined by Chesbrough (2003). Particularly, OI assumptions such as the wide distribution of innovative ideas, the lack of monopolistic ideas, the lack of timely discovery of innovative ideas to gain a competitive advantage, the selection of relevant business models based on their technological performance, and the perishability of intellectual property and services in the context of banks can be supported and discussed through the lens of BDA. The multi-dimensional context of BDA, with its ability to integrate into various organizational perspectives (external R&D, range of methods to create and advance intellectual properties, etc.), can explain diverging forms of OI (Barlatier et al. 2020).

Past research on firms practicing OI using BDA has highlighted that proactive participation in OI powered by BDA allows firms to interact with various organizations and professionals (Sun et al. 2020). From a banking perspective, this will help banks to create and monetize digital services, reduce costs, improve user experience, enhance business value, accelerate digital transformation, and place banks in an innovation position (Bogers et al. 2018b). Particularly, banks may follow the mechanisms of large firms to use BDA as an innovation fuel for strategic decision making for creating Fintech(ization), establishing state-of-the-art technology, and strengthening their mutual networks (Barlatier et al. 2020).

There are several data-driven organizations such as Tesla, AT&T, Cisco, and Linux that have benefited in the past from BDA to foster OI for building new products and services and offering a unique customer experience (Bogers et al. 2019). Contextualizing this to the banks (primarily described as data-driven entities) should consider leveraging BDA to accelerate OI for forecasting sales, planning and designing data-driven operations, creating new and innovative business models, and rectifying governance issues.

The integration of BDA into the OI process renders several benefits and challenges to organizations as well as banks. Generally, banks are criticized for their lack of transparency, which can be resolved by their participation in the OI process through BDA, ensuring that information is available across multiple platforms accessible to different stakeholders (Manyika et al. 2011). During the preliminary stages of OI, banks may benefit from BDA to pretest products' efficiency, which will help in overcoming performance issues (Yang et al. 2017). Moreover, market segmentation is a complex issue as it is directly related to customer satisfaction and profitability (Eriksson and Mattsson 1996), which can be addressed by implementing automated algorithms while banks embark on the OI process for customizing their products to fulfill the varying needs of different segments (Barlatier et al. 2020).

2.4. Theoretical Background and Hypotheses Development

This study employed a dynamic capability view (DCV) to empirically investigate the influence of BDA on creating and managing OIS in banks. DCV is an extension of Barney's (1991) resource-based view (RBV) theory, which is operationalized to explain the strategic progress of banks while contemplating a competitive advantage in a dynamic environment (Hitt et al. 2016; Teece et al. 1997). Based on the underpinning of DCV, we predict that the acquisition of strategic resources and the management of these resources are critical for the banks concerned to gain a competitive advantage while operating in a frequently changing environment. Past studies have used the fundamentals of DCV to outline BDA as a source of competitive advantage for organizations operating in a dynamic environment and requiring transparency (Akter et al. 2016; Dubey et al. 2019). However, the organizational surge in the acquisition of strategic resources to manage and streamline some of its key operations under the umbrella of OI remains unclear, which leads us to understand how BDA may influence the strategies for managing OI.

Subsequently, DCV logic is used to conceptualize BDA as a reflective construct and establish that the acquisition of strategic resources is essential in developing strategies pertaining to OI in banks (Barney 1991). Earlier studies have confirmed that firms concerned with designing OIS are required to manage their dynamic resources such as openness (Bogers et al. 2018a; Laursen and Salter 2006), selection of external partners (Sofka and Grimpe 2010), OI methods (Veugelers and Cassiman 1999), formalizing collaboration processes (Vlaar et al. 2007), and internal practices (Lakemond et al. 2016). Following this argument, BDA is used as a higher-order construct for linking the creation of OIS in the banks by managing these underlying factors and investigating their role in supporting the OI process (Figure 1).

Despite an established fact about the opportunities created by BDA in managing OI firms (Del Vecchio et al. 2018), the extant literature lacks empirical evidence about the potential and methods of harnessing BDA to promote OIS in the banks (Barlatier et al. 2020; Fasnacht 2018). A few recent studies in the banking sector have focused on highlighting the management of information and digital technologies at the organizational level to manage OI in banks and improve financial performance (Gianiodis et al. 2014; Martovoy et al. 2015; Naseer et al. 2021). Factors such as banks' openness (BOP), selection of external partners (SEP), open innovation methods (OIM), formalizing collaboration processes (FCP), and banks' internal practices (BIP) need to be investigated prior to discussing the actual impact of information and digital technologies acquired by the banks as a source of competitive advantage to support OIS.

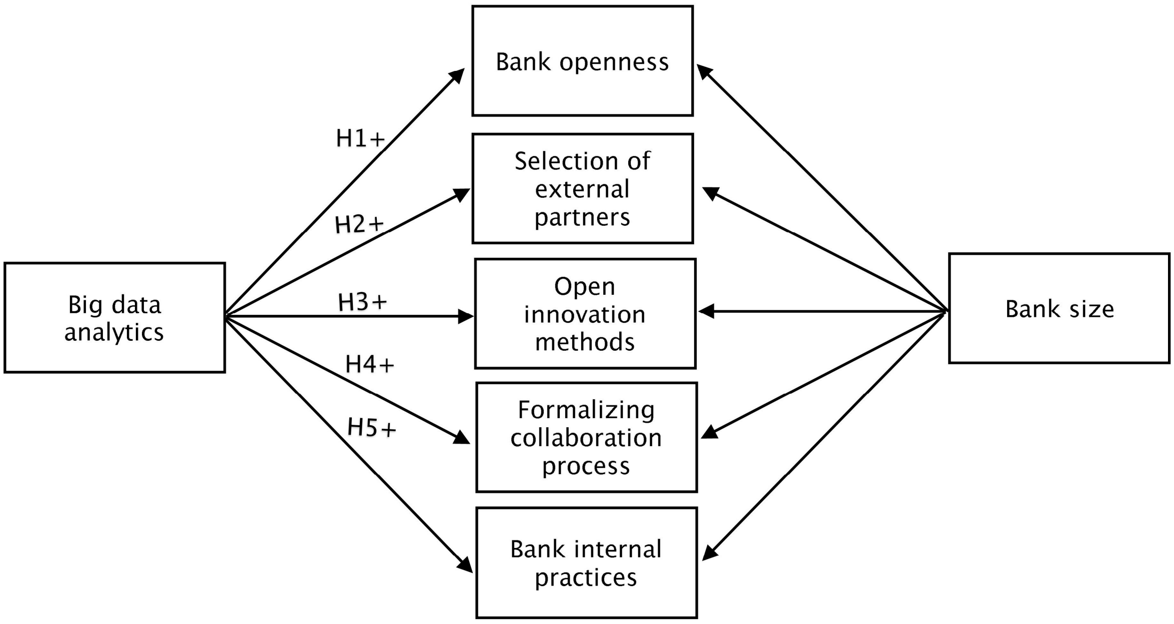

Figure 1. Theoretical model.

The studies on banks' openness (BOP) have linked it with the stability of the banking sector, financial development, reduction in bank risk, and stimulation of domestic competition allowing banks to produce a range of products and services (Bayraktar and Wang 2006; Bekaert et al. 2011; Luo et al. 2016; Ma and Yao 2022). Following the argument of banks' surge for the creation of openness, banks may strategically enhance their openness through OIS, as suggested by Bogers et al. (2018a) and Laursen and Salter (2006). However, enhancing BOP through OI requires information sharing among collaborating partners of banks' internal data, such as financial portfolios, products and services, and customers. Simultaneously, BDA, through its dynamic capabilities, may allow banks to enhance BOP, resulting in better banking stability, deep financial development, lower risk, and better domestic competition (Ali et al. 2021; Diebold et al. 2019; Shen and Chen 2018). This leads to proposing the first hypothesis (H1) as follows:

H1. *BDA has a significant positive impact on BOP to create effective OIS.*

While creating OIS, 21st-century organizations actively collaborate with numerous partners to build cooperative relationships with research and development (R&D) and their potential stakeholders, including customers, suppliers, competitors, and public institutions (Enkel et al. 2009). The selection of external partners (SEP) has been recognized as the most crucial aspect of creating OIS due to the complexities of knowledge required by the organizations and the fact that SEP significantly influences OIS capabilities and overall innovation (Lassen and Laugen 2017; Marina and Gulbrandsen 2013). Banks are known as multidisciplinary technology-implementing service entities producing a range of products and services having a short life cycle to fulfill dynamic market needs. Currently, banks do not possess the required capabilities to produce sophisticated products and services, which forces them to collaborate with external partners by creating effective OIS. However, the underlying complexities in the process of SEP based on the existing capabilities require leveraging smart and strategic resources enabled by BDA, as it allows the pretesting of products and overcoming performance issues, which may positively influence the creation of OIS (Yoon and Song 2014; Yang et al. 2017). Past studies have rendered different methods and approaches to SEP, such as morphology analysis (MA), generative topology maps (GTMs), effectuation, and causation, for creating effective OIS (Marina and Gulbrandsen 2013; Yoon and Song 2014). In this study, we predict that leveraging BDA to assess, screen, pretest, and evaluate SEP and strengthen their mutual networks may help banks in creating effective OIS (Barlatier et al. 2020). Thus, H2 is as follows:

H2. *BDA has a significant positive impact on SEP to create effective OIS.*

Open innovation methods (OIMs) are considered another key area to creating effective OIS and rely on organizations' internal capabilities and access to external sources and knowledge (Yildirim et al. 2022). Generally, organizations use three widely practiced OIMs (inbound, outbound, and a combination of both) to create OIS, and selecting an accurate OIM is critical due to the benefits associated with the identification of required capabilities, time, and overall innovation performance (Chesbrough and Bogers 2014; West and Bogers 2017). Past studies are yet to fully categorize the essential factors of an accurate OIM relevant to creating OIS. A few studies have attempted to highlight the issue by proposing organizational awareness and the nature of the project as the main criteria to consider during the selection of an OIM (Oztaysi et al. 2017; Yildirim et al. 2022). Practically, it is difficult to generalize and export these criteria to banks due to the differences in access and availability of the resources essential to select relevant OIM for authenticating OIS (León et al. 2020). Following the dynamic capabilities of BDA and banks' broad access to voluminous data from multiple platforms, it is predicted that BDA may act as a substantial tool to identify, select, test, evaluate, and correct relevant OIMs for creating effective OIS. Therefore, H3 is predicted as follows:

H3. *The BDA has a significant positive impact on OIMs to create effective OIS.*

Formalizing the collaboration process (FCP) is central to OIS as it ensures the success of OI processes and facilitates organizations in designing the right innovation structure (Bagherzadeh et al. 2021; Obradović et al. 2021). Recent studies have associated the identification of collaborating partners, shortage of experts, ambiguity of goals, organizational decision making, and governance structure with FCP (Brown et al. 2021). Alternatively, these factors can be described as organizational, legal, and regulatory barriers to FCP and can be managed by organizations' strategic resources such as information and knowledge. Banks are the most regulated entities as they follow various stringent internal and external formal regulations. Therefore, FCP in banks for creating effective OIS demand extra attention to overcome the heterogeneity issues, ensure effective portfolio and innovation management, and resolve governance issues. BDA offers a strategic solution to the organizations in the form of the availability of information and knowledge to be used as a tool for formalizing FCP for the identification of collaborating partners, people, goals, decision-making process, and governance structure, which will contribute to creating effective OIS. Hence, H4 is proposed as follows:

H4. *BDA has a significant positive impact on FCP to create effective OIS.*

The permeability of organizational boundaries has pushed organizations to consider multiple operational approaches to achieve a competitive advantage (Lu and Chesbrough 2022). This has resulted in a variety of business practices and models to manage the multidimensional operations of organizations. Particularly, service-oriented organizations (banks) operating in a dynamic business environment often face the critical issue of customer satisfaction, which drives them to design various OIS (Bogers et al. 2018b). In this regard, banks' internal practices (BIP) such as strategic resources, internal knowledge and skill, internal processes related to operations and governance, and manpower development to enhance skill may positively contribute to creating effective OIS (Barlatier et al. 2020). Additionally, banks operating in saturated markets are expected to park support for Fintech by integrating resources in a way that conforms to the emerging requirements of global competitive markets (Barlatier et al. 2020). Banks may achieve these goals by integrating the strategic resources available in the form of BDA to streamline BIP for creating effective OIS, which will help them to fulfill customers and market needs (Ali et al. 2021). Therefore, H5 predicts the following:

H5. *BDA has a significant positive impact on BIP to create effective OIS.*

3. Materials and Methods

The research hypotheses of this study were tested by employing a survey for data collection. The survey questionnaire was personally designed by the researchers and was pretested by distributing it to 4 academics and 4 banking industry professionals who were experts in the thematic areas of OI and were familiar with the applications of emerging digital technologies such as BDA in the banking industry. The content of the questionnaire was further improved based on experts' feedback, and the language and wording of the questionnaire were modified to remove complex statements. Once the questionnaire was ready for final data collection, the researchers sampled the bank executives employed in key managerial positions at Malaysian banks (offering a wide range of digital services and products to their clients) as the targeted population. Thus, this phase of designing a psychometrically accurate survey instrument and sampling the right population for data collection is considered crucial to achieving the objectives of the research.

Recently, the Malaysian banking industry has significantly transformed due to digitalization, and banks are expected to comply with the newly released guidelines of Bank Negara Malaysia's (BNM) Exposure Draft on Licensing Framework for Digital Banks (PWC 2020). Most of the banks in the country have digitalized their operations in the spirit of sheltering support to achieve Malaysia's Shared Prosperity Vision (SPV) 2030, maintain a competitive advantage, and ensure sustainable economic growth (Alam 2021). Additionally, the regulatory support in the form of the issuance of digital banking licenses (Koty 2021) and banks scaling up efforts to digitalize their operations certainly require banks to design strategies in the form of OI and acquire strategic resources such as BDA to offer an ultimate user experience to their customers.

3.1. Construct Operationalization

The researchers surveyed the literature sourced from popular databases, i.e., Scopus, Web of Science, and PubMed, using the keywords 'Big data analytics', 'open innovation in banks', and 'big data in banks'. This technique is valid as these databases are popular scientific outlets of novel studies in business, management, and different disciplines of OI and the financial sector (Tasya et al. 2023). The shortlisted studies were further reviewed to identify the measures for the survey instrument. All the constructs of our theoretical model were operationalized as reflective constructs. Table 2 presents the operationalized constructs of this study.

The survey instrument was separated into two sections (A and B). The demographic profiles of the respondents containing gender, age, educational level, job position, and job experience information were covered in Section A. Section B contains 25 items to measure the potential of BDA to support the creation of OIS in banks. Following the discussion in the theoretical model, the creation of OIS in banks relies on banks' openness (BOP), selection of external partners (SEP), open innovation methods (OIM), formalizing collaboration processes (FCP), and banks' internal practices (BIP), and BDA is projected to offer a supporting role in creating effective OIS. BOP was measured by 4 items adopted and modified from Enkel et al. (2009) and Yoon and Song (2014), SEP was estimated by 4 items adopted and modified from Yildirim et al. (2022), OIM was estimated by 4 items adopted and modified from Brown et al. (2021), FCP was measured by 4 items adopted and modified from Bogers et al. (2018b), BIP was estimated by 4 items adopted and modified from Lu and Chesbrough (2022), and BDA was estimated by 5 items adopted and modified from Akter et al. (2016). The participants were provided with a 5-point Likert scale (strongly disagree = 1 to strongly agree = 5) option to respond to these items.

Table 2. Construct operationalization.

Construct	Construct Label	Measures	Source
Banks openness	BOP	(BOP1) Our bank uses BDA to share information with collaborating partners of innovation projects. (BOP2) Our bank uses BDA to share financial portfolio data with external partners. (BOP3) Our bank uses BDA for sharing our products and services information with external partners. (BOP4) Our bank uses BDA to share corporate information with customers.	(Enkel et al. 2009; Yoon and Song 2014)
Selection of external partners	SEP	(SEP1) Our bank uses BDA for external partner screening to create open innovation strategies. (SEP2) Our bank uses BDA to match the selection of external partners with project needs. (SEP3) Our bank uses BDA to evaluate the performance of external partners. (SEP4) Our bank uses BDA to strengthen the mutual networks to ensure the success of open innovation projects.	(Yildirim et al. 2022)
Open innovation methods	OIM	(OIP1) Our bank uses BDA to identify the internal innovation practices relevant to the project. (OIP2) Our bank uses BDA to select and engage the key internal resources for an open innovation project. (OIP3) Our bank uses BDA to evaluate internal capabilities and identify project-specific capabilities. (OIP4) Our bank uses BDA to adjust internal capabilities and resources essential for an open innovation project.	(Brown et al. 2021)
Formalizing collaboration process	FCP	(FCP1) Our bank uses BDA to formalize the open innovation collaboration process. (FCP2) Our bank uses BDA to understand the legal requirements for collaboration. (FCP3) Our bank uses BDA to verify internal sources required to formalize the collaboration process. (FCP4) Our bank legal team uses BDA to ensure that formal collaboration requirements are fulfilled and are in line with the regulatory guidelines of the central bank.	(Bogers et al. 2018b)
Banks internal practices	BIP	(BIP1) Our bank uses BDA to identify the internal resources relevant for creating open innovation strategies. (BIP2) Our bank uses BDA to assess the existing knowledge and skill relevant to creating open innovation strategies. (BIP3) Our bank uses BDA to evaluate the governance practices relevant to creating open innovation strategies. (BIP4) Our bank uses BDA to assess and develop open innovation-related skills and competencies.	(Lu and Chesbrough 2022)
Big data analytics	BDA	(BDA1) Our bank continuously examines the open innovation opportunities through the strategic use of BDA. (BDA2) Our bank implements effective strategies to introduce and utilize BDA for open innovation. (BDA2) Our bank formally initiates the BDA planning process on how to implement it during open innovation projects. (BDA3) Our bank frequently adjusts open innovation strategies using BDA to better adapt to changing market conditions. (BDA5) Our bank has access to BDA sources essential to designing open innovation strategies.	(Akter et al. 2016)

3.2. Data Collection Process

The survey was administrated to the bank executives (marketing, customer relationship, business manager, branch managers) employed in key managerial positions at Malaysian banks licensed as digital banks. The executives of these banks were identified as the potential respondents for this research as these banks and their executives with managerial authorities have experienced implementing or are expected to implement BDA and cloud-based digital technologies in their strategic operations to comply with BNM's licensing requirements for digital banks and support digital strategies. Altogether, 622 samples were distributed to the executives employed at 21 different branches of 5 digital banks (CIMB, HSBC, Maybank, Alliance Bank, and OCBC) located in Selangor and Kuala Lumpur territories. The survey was conducted from 1 February 2022 to 21 March 2022 through social media platforms (LinkedIn, WhatsApp, Facebook, and Instagram) and e-mails. This method of data collection is considered efficient and reliable due to the ongoing COVID-19 pandemic and its efficacy in maintaining diversity and randomness in the responses (Ali et al. 2021). The participants returned 436 completed surveys, showing a response rate of 70.09%. We excluded 11 incomplete surveys during the data cleaning and preparation process and used 425 valid surveys for final data analysis. The method used for data collection and the survey response rate verified the validity of cases as the valid cases exceeded the minimum threshold of 200 to 400 cases, indicating 17 respondents for each indicator (Kline 2016). The non-response bias was checked by t-test to compare the difference between responding and non-responding participants and found no significant difference, as the p-value was >0.05 (Armstrong and Overton 1977). The demographic profiles of the respondents are reported in Table 3.

Table 3. Demographic profiles.

Demographic Character	N	Percentage
Gender		
Male	186	43.76
Female	232	54.58
Other	7	1.64
Age (years)		
Below 30	12	2.82
Between 30 and 35	56	13.17
Between 36 and 40	123	28.94
Between 41 and 45	163	38.35
Between 46 and 50	43	10.11
Above 50	28	6.58
Education level		
Diploma/certificate	48	11.29
Bachelor	246	57.88
Master	126	29.64
PHD	5	1.17
Job position		
Marketing manager	114	26.82
Customer relationship manager	109	25.64
Business manager	154	36.23
Branch manager	48	11.29
Job experience (years)		
Below 5	53	12.47
Between 5 and 10	92	21.64
Between 11 and 15	209	49.17
Between 16 and 20	47	11.05
Above 20	24	5.64

3.3. Data Analysis Procedures

Based on the exploratory nature of this research, PLS (partial least squares) technique is considered suitable due to relevantly higher accuracy in measuring the general model as compared to covariance-based SEM (Henseler et al. 2014). Further, SEM remains unaffected by model misspecification in certain parts of the proposed model. We categorized our study as exploratory due to the dearth of studies in the empirical literature exploring the influence of BDA in creating effective OIS. Therefore, we employed WarPLS version 7.0 to test our theoretical model and the research hypotheses. The PLS technique, also known as the prediction-oriented method, allows researchers to estimate the probability of the exogenous variables (Peng and Lai 2012). The current research is expected to measure the predictability or explanatory power of the antecedent factor (BDA). Since the literature is yet to empirically investigate the relationship between BDA and OIS, the theoretical foundation linking the association between these two variables is missing, which further justifies the appropriateness of employing a PLS-based modeling technique to analyze our data (Henseler et al. 2014). Finally, the higher accuracy of PLS in estimating a complex structural equation model, as proposed in this research, further justifies employing PLS. The model estimation was conducted in two stages following the procedures suggested by Peng and Lai (2012), Henseler et al. (2014), and Moshtari (2016). First, we evaluated the validity and reliability of the measurement model, and then we estimated the structural model.

4. Results and Discussion

4.1. Model Estimation

The first phase of analysis was to measure the validity and quality of the measurement model. To check the quality of the measurement model, we estimated scale composite reliability (SCR), Cronbach's alpha coefficients, and average variance extracted (AVE). Table 4 shows the results of the measurement model. We noticed that SCR and Cronbach's alpha coefficients were higher (>) than the threshold of 0.70; however, the AVE value for BDA was 0.48, which is slightly below the recommended criteria of 0.50. This indicated the reliability of the measurement model, as the latent construct explains 50% of the variance in items. The weak items with factor loading <0.5 were dropped and SEM analysis was reperformed to obtain new results, which are reported in Table 5. The results of new loadings were satisfactory as the values were >0.50 (Hair et al. 2017). Next, the correlations among major constructs were estimated and the results are presented in Table 6. It is notable that the leading diagonal entries representing square roots of AVE were greater than the inter-construct correlations. Therefore, it is argued that the discriminant validity of our measurement model is satisfactory.

Table 4. Initial factor loadings of the indicator variables (composite reliability) (AVE).

Variables	Measurements	Factor Loadings	Variance	Error	SCR	AVE
BDA	BDA1	0.73	0.53	0.57	0.85	0.48
	BDA2	0.22	0.06	0.94		
	BDA3	0.37	0.08	0.92		
	BDA4	0.82	0.64	0.36		
	BDA5	0.85	0.67	0.37		
BOP	BOP1	0.77	0.62	0.38	0.88	0.73
	BOP2	0.66	0.57	0.53		
	BOP3	0.62	0.58	0.58		
	BOP4	0.88	0.38	0.62		
SEP	SEP1	0.67	0.58	0.42	0.80	0.74
	SEP2	0.70	0.62	0.38		
	SEP3	0.78	0.67	0.37		
	SEP4	0.58	0.55	0.45		

Table 4. *Cont.*

Variables	Measurements	Factor Loadings	Variance	Error	SCR	AVE
OIM	OIM1	0.75	0.68	0.32	0.83	0.77
	OIM2	0.69	0.53	0.47		
	OIM3	0.66	0.55	0.45		
	OIM4	0.80	0.71	0.29		
FCP	FCP1	0.56	0.52	0.48	0.92	0.72
	FCP2	0.64	0.55	0.45		
	FCP3	0.53	0.51	0.49		
	FCP4	0.72	0.68	0.32		
BIP	BIP1	0.75	0.72	0.28	0.95	0.81
	BIP2	0.72	0.53	0.47		
	BIP3	0.79	0.69	0.31		
	BIP4	0.69	0.51	0.49		

Table 5. Factor loadings of the indicator variables (composite reliability) (AVE).

Variables	Measurements	Factor Loadings	Variance	Error	SCR	AVE
BDA	BDA1	0.73	0.53	0.57	0.88	0.57
	BDA4	0.82	0.64	0.36		
	BDA5	0.85	0.67	0.37		
BOP	BOP1	0.77	0.62	0.38	0.90	0.78
	BOP2	0.66	0.57	0.53		
	BOP3	0.62	0.58	0.58		
	BOP4	0.88	0.38	0.62		
SEP	SEP1	0.67	0.58	0.42	0.82	0.77
	SEP2	0.70	0.62	0.38		
	SEP3	0.78	0.67	0.37		
	SEP4	0.58	0.55	0.45		
OIM	OIM1	0.75	0.68	0.32	0.87	0.78
	OIM2	0.69	0.53	0.47		
	OIM3	0.66	0.55	0.45		
	OIM4	0.80	0.71	0.29		
FCP	FCP1	0.56	0.52	0.48	0.92	0.76
	FCP2	0.64	0.55	0.45		
	FCP3	0.53	0.51	0.49		
	FCP4	0.72	0.68	0.32		
BIP	BIP1	0.75	0.72	0.28	0.95	0.81
	BIP2	0.72	0.53	0.47		
	BIP3	0.79	0.69	0.31		
	BIP4	0.69	0.51	0.49		

Table 6. Correlations among major variables.

Constructs	BDA	BOP	SEP	OIM	FCP	BIP
BDA	0.76					
BOP	0.04	0.85				
SEP	0.27	0.37	0.83			
OIM	−0.07	−0.02	−0.09	0.84		
FCP	0.22	0.31	0.19	0.36	0.79	
BIP	−0.18	−0.10	−0.07	−0.23	−0.34	0.97

4.2. Common Method Bias (CMB)

CMB in survey-based research is impossible to address unless researchers use a number of informants for each observable item (Kock 2015). Different elements such as the consistency motif and social desirability may contribute to CMB (Kock 2015). Following Kock's (2015) criteria, we aimed to overcome CMB issues in our self-reported data in a way that its impact on final results can be minimized. First, respondents were requested to respond to our survey in accordance with the banks' meeting minutes or use information from official documents instead of using their personal experiences. Second, a statistical analysis (Harman's single-factor) was performed to estimate the CMB, and the results are presented in Table 7. The results indicated that the maximum covariance explained for the single factor was 37.75%, which confirmed that our results would remain unaffected by CMB.

Table 7. Results of single-factor Harman test.

Components	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	**Variance %**	**Cumulative %**	**Total**	**Variance %**	**Cumulative %**
1	10.563	37.754	35.754	10.563	10.563	35.754
2	4.432	4.456	68.792			
3	4.072	4.342	66.578			
4	3.458	3.073	64.518			
5	3.486	3.525	70.621			
6	3.464	3.514	68.563			
7	2.568	2.424	72.618			
8	2.382	2.603	73.673			
9	1.283	1.613	74.513			
10	0.881	1.357	76.667			
11	0.851	1.258	77.628			
12	0.743	2.415	81.736			
13	0.737	2.476	81.734			
14	0.626	1.723	80.539			
15	0.823	1.486	81.537			
16	0.856	1.658	77.854			
17	0.843	2.759	82.541			
18	0.844	3.619	78.624			
19	0.532	3.476	71.581			
20	0.634	5.638	83.673			
21	0.548	2.615	85.627			
22	0.664	2.584	78.636			
23	0.679	3.773	72.752			
24	0.534	3.361	76.736			
25	0.645	3.784	77.753			

Extraction method: principal component analysis.

4.3. Endogeneity Test

Prior to proceeding to the second phase of analysis (hypotheses testing), it is essential to test the endogeneity of the exogenous variable in the theoretical model of this study. Referring to the discussion in the literature review, BDA was conceptualized as an exogenous variable to BOP, SEP, OIM, FCP, and BIP instead of considering it the other way around, leading us to infer that endogeneity is not likely to be a concerning issue in this research. Further, we conducted the Durbin–Wu–Hausman test to support our assumption following Davidson and MacKinnon's (1993) approach. We regressed BDA with BOP, SEP, OIM, FCP, BIP, and a control variable (BS), and then the residuals of this regression were used as an additional regressor to test hypothesized equations. The parameter estimates for the residual were insignificant, establishing that the BDA was not endogenous in our model, consistent with the fundamental conceptualization of this study.

4.4. Hypotheses Testing

Next, we tested our hypotheses using the PLS-based bootstrapping technique to measure standard errors and the significance of parameter estimates (Chin 1998; Peng and

Lai 2012; Moshtari 2016). The significance of parameter estimates was measured using bootstrapping procedures instead of traditional parametric techniques as these are unable to assume the normal distribution of multivariate (Henseler et al. 2014). The results of PLS output obtained from WarPLS 7.0 are presented in Figure 2. It is notable that $R^2 = 0.724$, which indicates that BDA explains a significant amount of variance in BOP, SEP, OIM, FCP, and BIP. To test our hypotheses, we analyzed standardized β and ρ values of PLS output. The results of PLS estimates indicate that H1 (BDA → BOP) is supported (β = 0.615; ρ = < 0.001). Similarly, H2 (BDA → SEP) was also supported (β = 0.743; ρ = < 0.001), whereas H3 (BDA → OIM) is not supported (β = 0.042; ρ = > 0.001). The results of H4 (BDA → FCP) indicated that it is supported (β = 0.865; ρ = < 0.001), and the results of H5 (BDA → BIP) confirmed that it is not supported (β = 0.036; ρ = > 0.001).

The bank size (BS) was included in our theoretical model as a control variable. The results of the PLS estimate (Figure 2) confirmed that it is not significantly related to the BIP, SEP, OIM, FCP, and BIP. The path coefficients of PLS were obtained by running 500 bootstrap samples, and the results of standardized β and their ρ-values are summarized in Table 8.

Table 8. Structural estimates.

Hypothesis	Impact of	On	β	ρ	Supported/Not Supported
H1	BDA	BOP	0.615	<0.001	Yes
H2	BDA	SEP	0.743	<0.001	Yes
H3	BDA	OIM	0.042	>0.001	No
H4	BDA	FCP	0.865	<0.001	Yes
H5	BDA	BIP	0.036	>0.001	No

The explanatory power of our theoretical model was further examined by analyzing the explained variance (R^2) of endogenous variables. It is consistent with the PLS objective to use R^2 for assessing the structural model as it helps in maximizing the variance explained in endogenous variables (Chin 1998). The values of R^2 for BOP (0.617), SEP (0.674), OIM (0.542), FCP (0.783), and BIP (0.508) were moderately strong. The effect size of variance in each variable remains unexplored in the endogenous latent variables and can be evaluated by Cohen's f^2 formula. To estimate the effect size, we used Cohen's (1988) approach by considering large (0.35), medium (0.15), and small (0.02) values as thresholds to investigate the effect size of BDA on our endogenous variables. The results of f^2 (effect sizes) for BDA effect on BOP (0.628), SEP (0.697), and FCP (0.791) were considered large, whereas for IOM (0.049) and BIP (0.032), BDA had a medium-sized effect. We also estimated the predictability of our model using Stone–Geisser's Q^2 method and found that all our endogenous variables had an acceptable predictive relevance as the values of Q^2 were greater than zero (Peng and Lai 2012; Moshtari 2016). The results of R^2, f^2, and Q^2 are reported in Table 9.

Table 9. Summary of structural estimates.

Constructs	R^2	f^2	Q^2
BOP	0.617	0.628	0.635
SEP	0.674	0.697	0.712
IOM	0.038	0.049	0.055
FCP	0.783	0.791	0.808
BIP	0.029	0.032	0.038

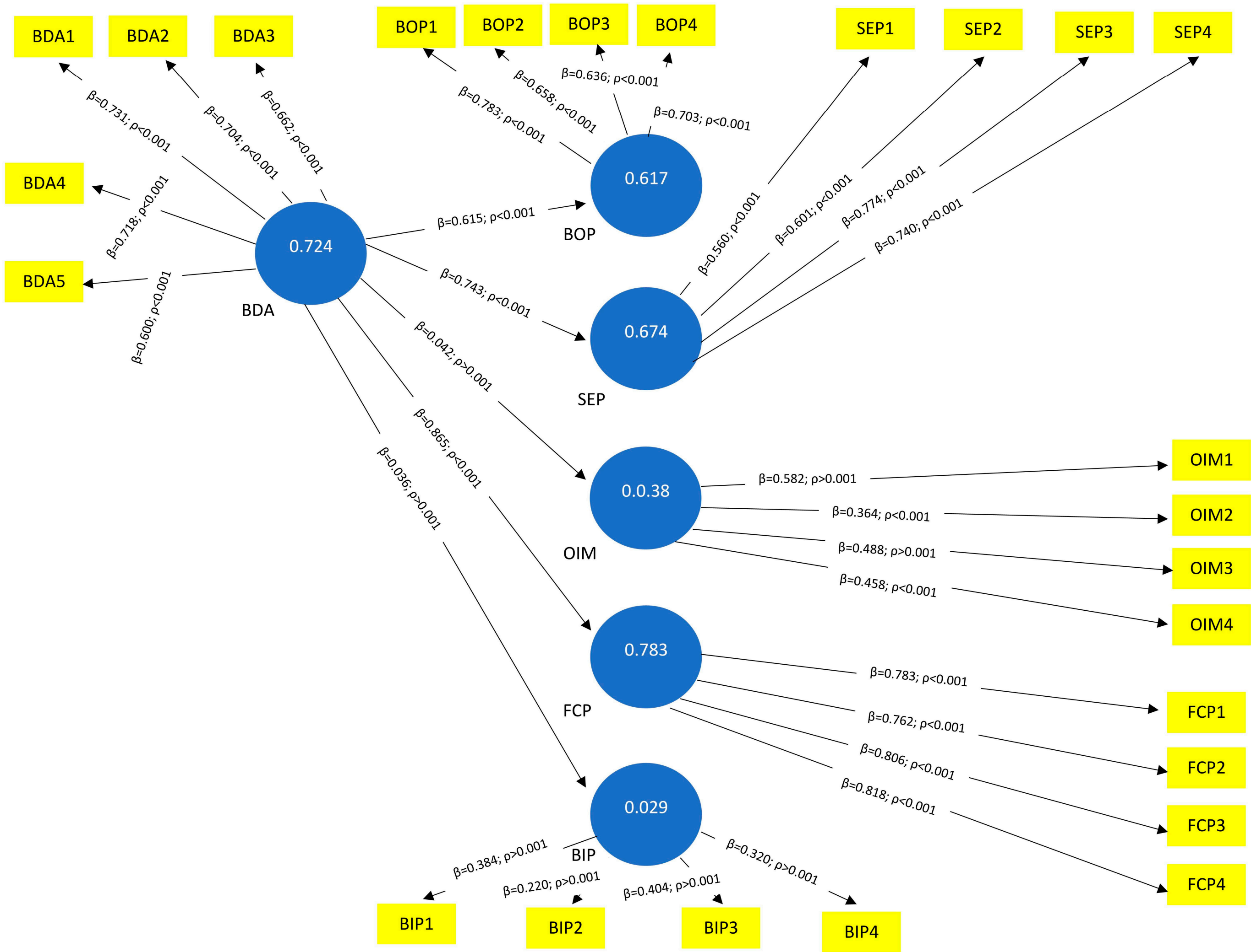

Figure 2. PLS estimates.

5. Discussion and Conclusions

The empirical findings of this study elucidate the significance of BDA as a strategic tool to create effective OIS in banks. Past studies (see Bigliardi et al. 2021; Capurro et al. 2022; Del Vecchio et al. 2018) have categorized BDA as a formative constructive essential to creating effective OIS. The current study conceptualized BDA as a reflective latent construct offering dynamic opportunities to the banks to create and manage OIS (Bogers et al. 2019). The results of this study suggest a significant positive relationship between BDA/BOP, SEP, and FCP (H1, H2, and H4), and an insignificant positive relationship between BDA/OIM, and BIP (H3, H5). Altogether, our results indicate that BDA provides a strategic tool to help banks in creating effective OIS by managing strategic components such as BOP, SEP, OIM, FCP, and BIP of OI. This finding validates the studies of Bogers et al. (2019) and Bogers et al. (2018a, 2018b), arguing that DCV as a dynamic organizational capability may help organizations manage their OIS through certain practices and policies (Teece et al. 1997). Based on this finding, we argue that banks seeking to address issues of service heterogeneity (Fasnacht 2018), developing innovative business models (Gianiodis et al. 2014), and improving their portfolio management (Damanpour et al. 2009; Priem et al. 2011; Sirmon et al. 2007) to diversify their products and services, enhance user experience, and adapt to the new normal should design OIS leveraging the unique features of BDA (OECD 2014).

The results of PLS path coefficients (Table 8) and the summary of impact sizes (Table 9) indicate that BDA has a significant positive impact on BOP, suggesting that BDA may help banks in enhancing their openness. This result validates the studies of Bayraktar and Wang (2006), Bekaert et al. (2011), Luo et al. (2016), and Ma and Yao (2022), arguing that OIS may help organizations to improve their openness level through active information sharing for better stability, financial development, reduced risk, and stimulated domestic competition. The results of BDA's impact on SEP determine that the selection of external partners while creating OIS should be assessed, screened, pretested, and evaluated through smart and strategic resources enabled by BDA (Yoon and Song 2014; Yang et al. 2017). This finding leads us to propose BDA as a unique strategic resource for organizations to select and collaborate with the right partners to access the required knowledge while creating effective OIS (Enkel et al. 2009; Lassen and Laugen 2017). Similarly, the finding on the impact of BDA on FCP (H4) revealed that it has a significant positive impact, establishing that banks may ensure the success of the OI process and design the right innovation structure by identifying and collaborating with the right partners (Bagherzadeh et al. 2021; Obradović et al. 2021). This finding corroborated that leveraging BDA to formalize organizations' collaboration processes during OI may help to address the issues of shortages of experts, ambiguity of goals, organizational decision making, and governance structure (Brown et al. 2021).

Contrary to our assumptions, BDA indicated an insignificant positive impact on OIM (H3) and BIP (H5), which deviates from the findings of Yildirim et al. (2022), Oztaysi et al. (2017), and Lu and Chesbrough (2022), who identified organizations' internal capabilities, access to external sources and knowledge, and significance of internal processes to create effective OIS. The finding leads us to predict that specifying OIM and identifying relevant internal practices to achieve organizational objectives may help in managing multi-dimensional business operations. However, the actual role of OIM and BIP in creating OIS remains an interesting prospect for future researchers and needs further investigation, particularly under the influence of BDA.

This study has investigated the role of BDA in creating OIS for banks through the fundamentals of RBV. First, we identified BOP, SEP, OIM, FCP, and BIP as the essential components to create effective OIS for the banks. Second, we proposed BDA as a strategic tool and empirically tested its impact on these strategic components. The statistical analysis elucidated that BDA is a strong and positive predictor of BIP, SEP, and FCP, whereas it is a medium and insignificant positive predictor of OIM and BIP, respectively. Contrary to our prediction, the findings indicate that OIM and BIP need further investigation to specify relevant methods and task-oriented internal practices for creating OIS leveraging BDA.

5.1. Research Contribution

Our findings offer several distinct contributions to the literature on the applications of BDA and OIS. Based on the theoretical nature of our research, this is the first study that has empirically determined the methods to create OIS in banks, which contributes to the knowledge of OI by adding new empirical evidence facilitated by BDA. Another significant contribution of this research is to the practical domains of the banking sector which continues to crumble in a competitive environment due to issues of service heterogeneity, lack of innovative business models, and poor portfolio management. The policy makers and managers in the banking sector may consider the insight of this study to address these issues through OIS using BDA as a strategic tool. Lastly, our findings have contributed to developing various research directions based on the highlighted limitations, which can be exploited to explore the untapped research areas related to the effects of BDA contingent to create OIS.

5.2. Theoretical Implications

From a theoretical lens, this study has validated the role of BDA in the management of effective OIS, confirming BDA as one of the key organizational capabilities, which is consistent with the views of DCV. The empirical results of this study delineate that BDA has a significant positive effect on BOP, SEP, and FCP, leading us to infer that the issues of service differentiation and customer experience optimization are managed effectively when banks potentially leverage BDA for these OI strategies. Additionally, banks are required to reconsider their OIM and BIP by employing BDA so that their OIS is effective in a way that the Fintechization process is smooth and that banks accelerate toward a successful digital transition.

5.3. Implications for Practice

The findings of our study offer various practical implications to the regulators, policy makers, and managers of banks. The regulators of banks may use this study as a guideline to create effective digital strategies for transitioning the financial sector and enhance its role in the economic development of the country by coupling OIS and BDA as a major strategic policy tool. The insight offered in this study will allow the regulators of banks to use BDA for enhancing openness to OI, identify the right collaborating partners, establish the required formal and legal infrastructure for OI, and streamline internal processes based on their objectives. The broad findings of our study will allow the policy makers of banks to use this study as a benchmark to diversify their products and services, optimize customer satisfaction, and develop matrices of better portfolio management. The managers of the banks consistently face the issue of developing key capabilities to reduce bank risk, overcome the shortage of experts, minimize goal ambiguity, improve organizational decision making, and strengthen governance structure by seeking knowledge from outside the banks using OI. The managers of banks may use the findings of this research to address these issues to streamline the OI process by using BDA as a strategic option. The bank professionals employed in key executive positions should consider different options to find methods to enhance their openness, select different collaboration partners, practice multiple internal methods, and use various formal legislations during their participation in OI. The prospects inferred in this study will allow these bank professionals to use BDA to authenticate these practices during the OI process.

5.4. Limitations and Future Research

The limitations of this research are related to the theoretical model, the research instrument, data collection methods, and data analysis procedures. First, our theoretical model mostly contains organizational-level variables to create effective OIS through BDA. The theoretical model was validated through various statistical procedures; however, based on the theoretical foundation of this study and the participants of this study, individuals' personal characteristics, such as technical competency, may play a significant role in fully understanding and engaging BDA to create OIS. Therefore, future studies are recommended to investigate the role (mediating/moderating) of technical competency while investigating the impact of BDA to create OIS. Second, the research instrument of this study was designed using the triangulation technique for achieving efficiency during data collection from the targeted sample, which may incur the issues of common method variance and the halo effect, leading to the poor generalizability of the results. To address these issues, we employed robust approaches such as the Harman single-factor analysis and the Durbin–Wu–Hausman test. Finally, the data collection procedures through convenience sampling may represent a lack of diversity in participants' responses. To diversify and ensure the randomness in participants' responses, the survey was distributed through different social media platforms and a statistical test was performed to overcome the biases in data collection.

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