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Perceptions of the Use of Quick Response Code Indonesian Standard (QRIS) for Payment and its Impact on Consumer Behavior

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Abstract

Currently the use of cash payments is starting to change to a simpler payment method to non-cash transactions, it is supported by digital payment technology that is developing very quickly. One of the payment methods that can be used through smartphones is using QR codes as a way of payment. Using a qualitative approach, this study aims to analyze the influence of usability, ease of use, and trust factors on consumer acceptance of QR and its impact on purchasing behavior through a qualitative approach. The results of this study show that most respondents, the majority of whom are male, live in the Greater Jakarta area, are between 36-45 years old, and work as government employees, have adopted QRIS through mobile banking. The main factors influencing adoption include ease of use, security, and convenience. The study also found that QRIS has been instrumental in improving financial inclusion and transaction efficiency, highlighting its potential to supporting the growth of the digital economy in Indonesia. The results of this study will contribute to the development of digital payments, especially based on the resulting perceptions and their impact on purchasing behavior.

Keywords: digital payments, mobile payments, qris, thematic analysis, user perceptions

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Introduction

In recent times, the development of new services in the banking and finance sector has been influenced by telebanking, online/mobile banking, and other types of financial technology (fintech). These advancements have enabled the sector to address the universal challenges associated with facilitating transactions across different industries, thanks to improved accessibility, speed, efficiency, effectiveness, and transparency (Mbaidin et al., 2023). These innovations also help lower operational costs and improve customer satisfaction by offering a more convenient and secure way to manage financial transactions. Fintech integration not only streamlines processes, but also brings new services that did not exist before, such as instant payments and digital wallets. These continued developments in the financial sector show how important technology is in shaping the future of banking and finance.

The high trend of digital shopping among consumers is made easier by advances in fintech. Transactions are now more practical without the need for cash by simply using a smartphone for payment through mobile payment applications or e-wallets (Mansour, 2022). Additional factors driving the increasing use of e-money are the current health and environmental situation, especially the COVID-19 pandemic, and social distancing policies that encourage the shift of payment transactions to the digital realm to reduce the risk of spreading the virus through cash. Data from 2021 shows a 69% increase in cashless financial services activity on commerce platforms, as well as a 65% increase in other payments such as electricity and water bills. Overall, there was a 300% increase in digital payment traffic (Rosmayanti, 2021).

The development of FinTech is accelerating in the context of digital transformation, making it easier for people to transact safely and efficiently. The growth of digital transactions, which goes hand in hand with an increase in e-commerce transactions, is especially noticeable during the COVID-19 pandemic. In a press conference at the beginning of 2023 on January 19, Bank Indonesia Governor, Perry Warjiyo reported that the value of electronic money transactions in 2022 increased by 30.84%, reaching Rp 399.6 trillion, and is expected to rise another 23.9% in 2023, to Rp 495.2 trillion. Meanwhile, the value of digital banking transactions in 2022 rose 28.72% from the previous year to IDR 52,545.8 trillion, with a projected growth of 22.13% in 2023, reaching IDR 64,175.1 trillion (Jannah, 2023).

One of the characteristics of using digital payments is that they are cashless. Cashless payments may vary from country to country. Cashless solutions can be classified based on the digitalization that the implementation environment requires, the payment technology as the latest solution, and the supporting infrastructure provided (Rafferty & Fajar, 2022). Quick Response Code Indonesian Standard (QRIS) is one method of non-cash payment and has been widely implemented. Bank Indonesia projects its focus on digital finance by 2025, including digitization of the banking sector and national digital economy-financial integration. However, based on the first quarter 2021 report from the Indonesian Payment System Association (ASPI), QRIS transactions in 2020 only reached 123.92 million, with a total nominal value of IDR 8182 trillion. This figure is still lower than debit card transactions, which in the same year recorded 6658 million transactions with a total nominal value of IDR 6243 trillion, of which 3999 million were cash withdrawal transactions with a nominal value of IDR 2991 trillion. This fact attracts attention considering that Bank Indonesia targets digital financial transactions as the main focus in 2025 (Tenggino & Mauritsius, 2022).

The banking sector continues to experience continuous digital evolution along with paradigm shifts in the banking sector (Malinka et al., 2022). Banking services consist of processing information and data, therefore, the development of commercial banking is obviously closely linked to the development of information technology. Processing information and data has always been at the heart of banking activities. For example, the opening of deposit accounts allows banks to collect information and data, which they use to expand their operations, including correspondent banking and electronic fund transfers (Yamaoka, 2023).

The regulation of payment services is governed by the principles of commercial law applicable in each country. The services and types of transactions include a Real-Time Gross Settlement System (RTGS), electronic payments, local and international cards, mobile payments, and wallets (Simatele & Mbedzi, 2021). Digital financial services can also help customers increase their income by offering loan and

savings services, easy payment methods, and so on (Yunping Hao & Yin, 2023). Thus, the use of digital payment systems will be a development trend that can facilitate the payment process.

The importance of further investigating usability, ease of use, and trust in the context of QRIS is based on a few key reasons. First, digital payment technology continues to evolve rapidly, and an in-depth understanding of these factors can help improve user adoption and satisfaction. Second, while QRIS has been widely implemented, there are still challenges that need to be overcome to ensure this technology can be used effectively and safely by different segments of society. Lastly, these factors play an important role in shaping consumer perceptions and behavior, which in turn may affect the successful implementation of QRIS in Indonesia. By further understanding how usability, ease of use, and trust affect QRIS acceptance, this research is expected to provide valuable insights for policymakers, industry practitioners, and technology developers to improve this digital payment system. An in-depth investigation into these factors will also help identify areas that require improvement and strategies that can be implemented to encourage wider adoption and more effective usage.

This study aims to find answers to the research questions, namely: (1) How do factors such as usability, ease of use, and trust affect the acceptance of QRIS by consumers? Additionally, this study seeks to understand (2) How does the use of QRIS affect consumer purchasing behavior in the payment system? This research question will be answered through a qualitative approach in accordance with the methodology utilized.

This research makes a significant contribution, both theoretically and practically. Theoretically, this research deepens the understanding of the factors that influence QRIS adoption, such as ease of use, trust, and usability. In addition, this research presents a theoretical framework that explains the changes in consumer behavior due to the use of digital payment methods, specifically QRIS, and provides an evaluation model to measure the overall impact of QRIS implementation. From a practical perspective, this research provides valuable guidance for the government and other stakeholders to address challenges such as security, network limitations, and consumer education. The research also encourages improved accessibility to expand the reach and adoption of QRIS, especially for MSMEs, and helps identify strategic measures for more effective implementation. The study also emphasizes the importance of recommendations to improve transaction security and system stability to encourage user trust, which is essential for the continued use of QRIS.

Literature Review

Digital Payments

Digital payments are increasingly becoming a habit in people's daily lives. This rapid development in the financial sector has resulted in various digital payment technologies, where both the sender and receiver of money use digital applications to make transactions (Khando et al., 2023). The development of a sophisticated payment system is essential to maintaining the strength and efficiency of the national payment system in order to achieve sustainable, comprehensive development and contribute to supporting Gross Domestic Product (GDP) growth (Lutfi et al., 2021). Several studies have examined the broader context of cashless payment methods, including mobile payments and digital wallets. Khando et al. (2023) conducted a systematic literature review on challenges and emerging technologies in digital payments, emphasizing the role of security and user experience in technology adoption. Similarly, de Luna et al. (2019) discussed factors that influence the adoption of mobile payment systems, such as perceived ease of use and perceived usefulness.

Digital payments and online banking have become omnipresent with the rise of digital and online services and the decline in the use of cash, and access to payments needs to evolve in parallel to remove barriers to participation in society (Dai et al., 2023). The changing patterns of the new digital ecosystem are forcing the banking sector to adapt to new business models that take into account the needs of digitization and rethink their core services and processes in order to better interact with customers (Stefanelli & Manta, 2023). In addition, financial institutions are now using advanced technologies such as AI and machine learning to improve the customer experience and increase operational efficiency. This digital transformation involves not only implementing new technologies, but also creating a culture

of innovation and flexibility within the organization. With this approach, banks can remain competitive and meet the needs of customers who are increasingly sophisticated in their use of technology.

Banks are therefore constantly shifting to a service delivery mix that is increasingly oriented towards the digitization of their service products. The main strategy pillars oversee the reduction of physical desks, the increase of services provided through ATMs, and the improvement of interfaces for customers, such as the improvement of payment devices in electronic payment transactions. All these changes have been enhanced by the outbreak of the pandemic, which reduced and resized the physical activities of financial intermediaries and increased consumer attitudes towards digital and mobile retail banking (Stefanelli & Manta, 2023).

Ultimately, digital payments have reduced the role of intermediaries in evaluating customer profiles and product suitability to a more efficient one. This is partly because payment systems are closely linked to the broader impact of technology on the financial industry and public services (Miglionico, 2023). In addition, the automation and data analytics features in digital payment systems enable faster and more accurate assessments of customer needs and preferences. With the integration of these technologies, financial institutions can provide more customized and relevant products and services, which in turn increases customer satisfaction and loyalty. As a result, the efficiency and effectiveness of financial operations have significantly improved.

Transaction costs are also one of the challenges in the payment system. These include fees for cross-border fund transfers through correspondent banking, fees associated with international credit cards, and various fees stemming from currency exchange and physical cash handling (Yamaoka, 2023). As a solution, decentralized and competitive cost creation mechanisms (Zilnieks, 2020), considering policies to encourage the widespread use of digital payment instruments (Simatele & Mbedzi, 2021), as well as the use of technological applications to automate transactions and the transmission of necessary information to authorities, can be considered to reduce transaction costs (Miglionico, 2023).

From an organizational perspective, collaboration between financial institutions and regulators is essential to effectively address the challenges posed by technology and to ensure its responsible and sustainable utilization for the benefit of all stakeholders (Dananjayan et al., 2023). As traditional financial institutions gradually increase investment in FinTech, the integration of emerging technologies and traditional financial services increases, reflecting the technology spillover effect that can improve the efficiency of financial institutions (Yi Hu Wu & Chen, 2023). In addition, this cooperation contributes to creating a more stable and secure financial environment by encouraging innovation while remaining compliant with existing regulations. It also enables financial institutions to more effectively adapt to rapid technological changes and maintain competitiveness in the market. Through this collaboration, stakeholders can develop a more robust risk management framework and improve the overall resilience of the financial system.

In terms of technology, to reduce costs and increase efficiency, the use of technology has the potential to revolutionize a large number of conventional banking services now available by improving transaction security, speeding up transfer times, and doing so at a fraction of the cost (Mbaidin et al., 2023). In addition, advanced technologies such as blockchain and artificial intelligence can increase transparency and accuracy in financial transactions. These innovations not only simplify processes, but also increase the level of trust and reliability for customers. As a result, the financial sector is able to provide more personalized and efficient services, meeting the changing needs of the market.

Mobile Payments

In recent years, mobile phones have become not only a communication tool but also a payment tool for most people. Payments made through mobile phones have become a part of people's daily lives (Zhong & Moon, 2022). Mobile payments can be defined as business activities involving electronic devices connected to mobile networks that enable the successful completion of economic transactions (de Luna et al., 2019).

A typical mobile banking solution differs from the existing types of mobile payment solutions, as the former mainly allow web-based access to banking transactions using mobile connectivity. On the other

hand, mobile payment applications open up the possibility of enabling financial transactions in more settings (De et al., 2015). Mobile banking mainly serves to provide users with access to bank accounts and related services, such as checking balances, making fund transfers, and paying bills. In contrast, mobile payment apps are designed to facilitate various financial transactions directly at the point of sale or through transfers between individuals. This distinction demonstrates the flexibility and breadth of use of mobile payment apps in the modern financial context.

Mobile devices include mobile phones, PDAs, wireless tablets, and other devices that can connect to mobile telecommunications networks and enable payments to be made. In addition, the landscape of the m-payment industry has been changing rapidly with the introduction of new technologies, new business models, new applications, and the rise and fall of business ventures (Au & Kauffman, 2008). The rapid changes in this environment have driven major innovations, such as contactless payments and digital wallets, which have changed the way consumers and businesses transact. With these technological advancements come new opportunities and challenges that require industry players to constantly adapt to remain competitive. In addition, regulations are constantly updated to keep up with these technological developments, ensuring payment systems remain safe and trusted.

QRIS

A QR code is a set of codes that may be scanned with particular tools and contain data or information, such as the identification of the merchant or user, a nominal payment, and currency (Sofwatunnisa et al., 2023). Previous research has explored various factors that influence the acceptance of Quick Response Code Indonesian Standard (QRIS) as a digital payment method. For example, de Luna et al. (2019) found that technology usability significantly affects user adoption. Sofwatunnisa et al. (2023) also highlighted that the ease of use of QRIS increases user satisfaction. Research by Khando et al. (2023) also found that ease of use is a major factor in the adoption of digital payment methods. Another study by Tenggino & Mauritsius (2022) focused on consumer trust and the impact of social influence on QRIS adoption. In another sense, QR codes are storage systems that use dot matrix or two-dimensional bar codes developed by Denso Wave that can be printed or displayed on a screen and interpreted by a specialized reader to provide more extensive information than that found in traditional bar codes (Liébana-Cabanillas et al., 2015).

QR code payments are gaining popularity as mobile phones become more popular, which also invites more innovation in payment systems. QR code payments have several advantages over traditional payment systems. Among them is its convenience and security, it also allows cashless transactions, which reduces the risk of theft and fraud (Sofwatunnisa et al., 2023). The value of QR code payments extends to more efficient and faster services, increasing productivity and reducing transaction costs (Rafferty & Fajar, 2022).

Response Code in Rapid Using a QR code, the Indonesian Standard (QRIS), often known as QRIS or frequently pronounced KRIS, unifies several varieties of QR from different Payment System Service Providers (PJSP). The development of QRIS by the payment system industry and Bank Indonesia aims to make transactions with QR codes simpler, quicker, and more secure (Sofwatunnisa et al., 2023). This standardization reduces confusion among consumers and merchants by providing a unified QR code system that can be used across multiple payment platforms and providers. In addition, the implementation of QRIS expands financial inclusion by allowing small and medium-sized enterprises (SMEs) to accept digital payments more easily. As a result, QRIS supports the increased use of cashless transactions in Indonesia, driving the creation of a more modern and efficient payment ecosystem.

Methodology

This research adopts a qualitative approach to explore the use of QRIS in payment transactions and its impact on consumer behavior. This approach was chosen for its ability to provide an in-depth and contextualized understanding of social phenomena. Through this method, the research aims to gain data-driven qualitative insights into how factors such as usability, ease of use, and trust influence the acceptance of QRIS by consumers. The selection of these three factors is based on several theoretical frameworks that have been recognized in the literature, such as the Technology Acceptance Model

(TAM). This model was developed by Davis (1989) and states that the two main factors that influence technology acceptance are Perceived Usefulness and Perceived Ease of Use. TAM has been widely used in research on technology adoption to explain how these factors influence user intentions and behavior (Wicaksono, 2022):

1. Usability:
   Usability refers to the extent to which a technology can be used easily and efficiently by users. In the context of digital payments like QRIS, usability is very important as it affects the user experience and their desire to continue using the technology.
2. Ease of Use:
   Ease of use refers to the user's perception that using the technology does not require much effort. Technology that is easy to use is more likely to be accepted by users as it reduces barriers to adoption.
3. Trust:
   Trust is a critical factor in technology adoption, especially in the context of digital payments. Users must feel confident that their transactions are secure and that their personal data is protected. Without trust, the adoption of digital payment technology will be hindered.

The target respondents in this study are consumers who actively use QRIS. The research focuses on their experiences and perceptions regarding the use of QRIS to ensure that the data collected covers a wide range of user perspectives. This selection of respondents aims to get a comprehensive picture of the acceptance and influence of QRIS in consumers' daily lives. Details of the respondent criteria in this study are as follows:

1. QRIS Active Users: Respondents must have used QRIS to make payments at least once in the last six months.
2. Domicile: Respondents who live in Jabodetabek and its surroundings to ensure representation of areas with high QRIS adoption.
3. Age: Respondents were aged between 18 to 55 years old, to cover a diverse age group relevant to the use of digital payment technology.
4. Occupation: Respondents with various employment backgrounds, such as government employee, civil servants, private employees, self-employed, and students, to get diverse perspectives.
5. Education: Respondents should be at least high school graduates or equivalent to ensure an adequate understanding of digital technology.

The research process involved several key stages, starting with a clear and defined problem formulation. Following this, a literature review was conducted to build a strong theoretical foundation and shape the research model. Subsequently, the data was aggregated to gain thorough insight. The data obtained was then analyzed using appropriate statistical tools to validate the research hypotheses. The findings are then interpreted and discussed in the context of the existing literature, resulting in useful conclusions and recommendations for future research.

Data Collection

The data collection stage involved direct interaction with respondents, followed by careful and structured data analysis. The research concludes with the formulation of logical conclusions and practical suggestions. This research flow began with a clear identification of the problem and a literature review to develop an in-depth understanding of the topic. Next, a framework was developed as a basis for data collection. Data collection was conducted through a questionnaire with open-ended questions, which was disseminated through the WhatsApp social network. After data collection, data calculation and analysis were conducted to generate weighted conclusions and suggestions. The list of questions can be seen in Table 1, which is divided into 3 sections: the first section is a demographic questionnaire containing 11 questions, the second section is a short questionnaire containing 9 questions, and the last section is a free-form interview question section so that it can be answered as fully as possible, containing 3 questions.

The research instrument consisted of research questions designed in an open-question format to allow respondents to convey their experiences and opinions freely and in depth. Initially, this research was planned to collect data through semi-structured interviews to gain in-depth and contextual insights into

users' perceptions of QRIS. However, due to time constraints that did not allow for direct interviews with each respondent, the data collection format was adapted to open-ended questions via Google Form.

Although the data collection method was changed, the main objective remained the same, which was to get in-depth responses from the respondents. In the open-ended question format provided through Google Form, respondents were given the freedom to answer in the same way as in semi-structured interviews. The questions were designed to explore user experience, perceptions of usability, ease of use, and trust in the QRIS. Respondents were able to provide detailed and expressive answers, allowing for in-depth qualitative analysis.

This customization ensures that even if the data collection method changes, the quality and depth of the information obtained are maintained. This approach also allows for the collection of data from more respondents in less time, increasing the representation and validity of the research results. Steps Taken:

1. Questionnaire Design: The questionnaire was designed with open-ended questions that allowed respondents to provide in-depth and context-rich answers.
2. Questionnaire Distribution: The questionnaire was distributed via Google Form using the WhatsApp social network, reaching a wide range of respondents easily and quickly.
3. Data Analysis: The data collected was analyzed using thematic analysis methods, identifying key themes that emerged from respondents' answers.

With these changes, the research was still able to achieve the objective of identifying factors that influence QRIS acceptance by consumers as well as providing recommendations for the improvement of this digital payment system.

Table 1. Questionnaire Questions List

Questions List	**Revision**	**Data Collection Procedure**
Name/Initials (Optional)		Short answer text
Current email (if any)	Email (Optional)	Short answer text
Phone Number for respondent validation (Optional)		Short answer text
Gender	Radio Button: ○ Male ○ Female	
Domicile	Radio Button: ○ Jakarta, Bogor, Depok, Tangerang, Bekasi (Jabodetabek) ○ Java Island (Non-Jabodetabek) ○ Others: ...	
Age	Radio Button: ○ < 18 years old ○ 18 - 25 years old ○ 26 - 35 years old ○ 36 - 45 years old ○ 46 - 55 years old ○ > 55 years old	
Occupation	Radio Button: ○ Junior/Senior High School Students ○ College student ○ Entrepreneurship ○ Civil Servant ○ Private employee ○ Housewife/husband	

Questions List	**Revision**	**Data Collection Procedure**
	○ Not Working/Retired ○ Others: …	
Monthly income (in IDR)	Radio Button: ○ < 1.000.000 ○ 1.000.000 - 3.000.000 ○ 3.000.000 - 5.000.000 ○ 5.000.000 - 10.000.000 ○ 10.000.000 - 20.000.000 ○ > 20.000.000	
Latest education	Radio Button: ○ Junior high school/middle school/equivalent ○ Senior/vocational high school/equivalent ○ Associate degree/Diploma ○ Bachelor degree ○ Master degree ○ Doctoral degree ○ Others: …	
Have you ever made a payment using QRIS before?	Radio Button: ○ Yes, I have ○ Never	
The app you use more often for QRIS transactions:	Radio Button: ○ Mobile Banking (BCA Mobile, Livin Mandiri, BRIMo, BSI Mobile, etc) ○ e-Wallet (OVO, Dana, ShopeePay, GoPay, etc) ○ Others: …	
Does using QRIS make you pay faster?	Radio Button: ○ Yes ○ No	
Does QRIS make your transactions easier?	Radio Button: ○ Yes ○ No	
Does QRIS transactions save your time and energy?	Radio Button: ○ Yes ○ No	
Are you happy with the QRIS service?	Radio Button: ○ Yes ○ No	
Overall, are you satisfied with payment through QRIS (security and privacy)?	Radio Button: ○ Yes ○ No	
Do you often read or hear comments from other buyers/consumers about QRIS?	Radio Button: ○ Yes ○ No	

Questions List	**Revision**	**Data Collection Procedure**
Is using QRIS completely under your control?	Radio Button: ○ Yes ○ No	
Do you believe that QRIS is safe to use?	Radio Button: ○ Yes ○ No	
Do recommendations from family or friends influence you to use QRIS?	Radio Button: ○ Yes ○ No	
What do you think are the advantages of QRIS payments?		Long answer text
What do you think are the disadvantages of QRIS payments?		Long answer text
What suggestions or input can you provide for the development and performance improvement of payments with QRIS?		Long answer text

Data was collected through a questionnaire distributed via WhatsApp, utilizing the reach and accessibility of this platform to reach a wide range of respondents. This method was chosen for the efficiency and ease of collecting responses in a relatively short period of time, as well as to ensure higher engagement from respondents. The use of WhatsApp enabled direct communication and follow-up with participants, which improved the quality of the data obtained. The affordability and familiarity with the platform also encouraged higher response rates, making it an effective tool for gathering in-depth information from a diverse group of respondents.

Data Analysis

The collected data was analyzed using thematic analysis, an effective method for identifying and exploring themes in qualitative data. This process involves systematically coding the data to uncover significant patterns and trends in respondents' answers, which helps in drawing relevant and well-founded conclusions. In addition, thematic analysis allows for a deeper understanding of the context and nuances in the data, providing insights that may not be apparent with quantitative analysis alone. By categorizing and interpreting these themes, researchers can build a comprehensive narrative that answers the research questions as well as contributes to the broader field of study. This method also ensures that respondents' views are accurately represented and integrated into the research findings.

The process of thematic analysis begins with a thorough understanding of the data, followed by a coding process to identify concepts and categories. Once the codes are established, a search for themes is conducted to find patterns that appear consistently in the data. This process allows for the grouping of information into themes that are relevant and informative to the research.

In this study, the first step in data analysis was data transformation and selection, which involved the process of cleaning the data to ensure the accuracy and relevance of the information obtained. Next, the data was coded by grouping similar answers into common themes. This process enabled the identification of significant patterns in the respondents' answers. Finally, data visualization was conducted to facilitate the interpretation of the analysis results. This process provides an effective graphical representation of the research findings (Klepek & Bauerová, 2020). The entire thematic analysis process in this research was carried out manually using Microsoft Word and Microsoft Excel tools. In addition, this process also uses the researcher's personal interpretation skills.

Results

Questionnaire Results and Thematic Findings

From the results of the questionnaire involving 40 respondents, 40 thematic units were obtained that reflect the perception of QRIS usage. Frequency analysis showed that 87.78% of respondents gave a positive response to QRIS usage, confirming that factors such as usability, ease of use, and trustworthiness were well received by the majority of consumers. In contrast, 12.22% of respondents gave a negative response, highlighting areas that require improvement. The influence of QRIS on consumer purchasing behavior was seen to be significant, with 50% of respondents prioritizing the ease and practicality factor in its use. However, 26.83% of respondents highlighted network issues and system stability as key areas of concern. Results of demographic data collection, short questionnaires, and open-question interviews can be checked in Table 2.

In this study, the data saturation of 40 respondents was achieved through a systematic and diverse approach as well as in-depth thematic analysis. We ensured that the respondents reflected a sufficiently diverse population, and the analysis was conducted in stages to monitor data saturation. With this approach, we are confident that the data collected is sufficient to provide deep insights into the factors influencing QRIS acceptance. The following are some of the steps that have been taken to ensure data saturation in this study:

1. Phased Data Collection:
   Data were collected gradually and analyzed in parallel to identify when no more themes or new information emerged. This approach allowed the researcher to observe when data saturation began to occur.
2. Diverse Profile of Respondents:
   Respondents were selected from a variety of demographic backgrounds, including age, gender, occupation, and geographic location. This diversity helps ensure that various perspectives and experiences are represented in the data.
3. Thematic Analysis:
   Using thematic analysis, the data obtained from the 40 respondents was analyzed to identify key emerging themes. This analysis was conducted until no more new themes were identified, indicating that data saturation had been reached.
4. Consistency of Findings:
   Consistency in answers and emerging themes from respondents indicates that data saturation has been achieved. When most respondents give similar answers or raise the same issues, this indicates that sufficient information has been collected.
5. Feedback and Validation:
   Validation of the findings was done by seeking feedback from several respondents on the conclusions drawn. This helps to ensure that the interpretation of the data is in line with the respondents' experiences and views.

From the demographic shown in Table 2, it shows that the majority of respondents are male, domiciled in the Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek) areas, with an age range of 36-45 years old, and the majority have jobs as private employees. In addition, the majority of respondents have an income of 10-20 million Rupiah with an educational background of bachelor, and the majority of respondents have used QRIS through mobile banking. This demographic profile indicates that the respondents have a high level of financial stability and good access to technology. In addition, the widespread use of mobile banking for QRIS transactions reflects the increasing adoption of digital payments in urban areas. Understanding these demographic characteristics is important to customize financial services and strategies to suit the specific needs and preferences of this user segment.

Table 2. Demographic Data

Description	Content
Gender distribution of respondents	Male: 62.5%; Female: 37.5%
Domicile distribution of respondents	Jabodetabek: 77.5%; Java Island (Non-Jabodetabek): 10%; Others: 12.5%
Age distribution of respondents	36-45 years old: 45%; 26-35 years old: 40%; 18-25 years old: 7.5%; 46-55 years old: 5%; >55 years old: 2.5%
Occupation distribution of respondents	Government Employee: 47.5%; Civil Servant: 12.5%; Housewife/husband: 10%; College Student: 5%; Private Employee: 5%; Others: 20%
Monthly income distribution of respondents (in IDR)	10.000.000 - 20.000.000: 42.5%; 5.000.000 - 10.000.000: 32.5%; 3.000.000 - 5.000.000: 10%; >20.000.000: 10%; 1.000.000 - 3.000.000: 5%
Educational background of respondents	Bachelor degree: 62.5%; Master degree: 25%; Associate degree/Diploma: 10%; Senior/vocational high school/equivalent: 2.5%
Experience using QRIS	Yes: 97.5%; No: 2.5%
Preferred app for QRIS transactions	Mobile Banking: 73.7%; e-Wallet: 23.7%; ATM: 2.6%
Transaction speed; Ease of transactions; Time and energy saving; Happy with QRIS service; Overall satisfaction with QRIS; Comments from others about QRIS; Control over QRIS usage; QRIS safety; Influence of recommendations	Transaction speed: 95% satisfied; Ease of transactions: 97.5% satisfied; Time and energy saving: 92.5% agree; Happy with QRIS service: 100% satisfied; Overall satisfaction with QRIS: 100% satisfied; Comments from others about QRIS: 52.5% positive; Control over QRIS usage: 97.5% agree; QRIS safety: 95% confident; Influence of recommendations: 60% influenced

Suggestions and Feedback from Respondents

The analysis results show that respondents provide valuable suggestions to stakeholders, such as the industry and regulators, to improve the QRIS system in the future. The survey results show that 17.31% of respondents suggested increased security, and 13.46% emphasized the importance of flexibility and accessibility. Socialization, better education, and regulations for SME outreach were also suggested by 13.46% of respondents. While 11.54% suggested increasing the reach of QRIS to the SME sector, 9.62% wanted transaction simplification. A total of 5.77% of respondents urged the removal of administrative fees, improvement of network speed and reliability, and expansion of QRIS overseas. In addition, 3.85% wanted the maximum payment limit to be raised, while another 13.46% felt QRIS was sufficient. Table 3 summarizes 40 themes from 40 respondents, with common answers reflected in the questionnaire.

Table 3. The Most Frequent Responses in Thematic Units (Source: Own Research)

Number	Inquiry	Thematic Unit	Typical Responses
1	Using QRIS makes paying faster	Faster than other payment methods	Yes
		Not faster than other payment methods	No

Number	Inquiry	Thematic Unit	Typical Responses
2	QRIS makes transactions easier	Easier than other payment methods	Yes
		Not easier than other payment methods	No
3	QRIS saves time and energy	Saves more time and energy than other payment methods	Yes
		Not more time and energy efficient than other payment methods	No
4	Consumers are happy with QRIS services	Happy with QRIS service	Yes
		Not happy with QRIS service	No
5	Overall satisfied with QRIS payments (security and privacy)	Satisfied with QRIS	Yes
		Not satisfied with QRIS	No
6	Often read or hear comments from other buyers/consumers about QRIS	Read/hear QRIS comments	Yes
		Did not read/hear QRIS comments	No
7	Using QRIS is entirely within the control of the consumer in question	In full control	Yes
		Not in full control	No
8	QRIS is safe to use	QRIS is safe	Yes
		QRIS is not safe	No
9	Recommendations from family or friends influence to use QRIS	Other people's recommendations influence the use of QRIS	Yes
		Other people's recommendations do not affect the use of QRIS	No
10	Advantages of QRIS payment	Easy & Practical	"Practical, simple, "Ease of Shopping", "Practical and faster"
		Transaction Speed	"Fast and easy, "Fast, Easy, Cheap, Safe, Reliable", "Fast nominal right and no need to prepare a lot of cash in the pocket"
		Security	"Safe, easy and efficient, "Simple and safe", "Easy, cashless, safe"

Number	Inquiry	Thematic Unit	Typical Responses
		Recorded Transactions	"More practical and efficient for payment transactions and recorded transactions on the application", "Recorded in mutations"
		Universality & Anonymity	"Universal platform, even though it looks anonymous, it is still neatly recorded on the related platform"
11	Disadvantages of QRIS payments	Administration Cost	"Sometimes some sellers have admin fees"
		Network/signal/system Dependency	"If the network errors, "If the network is bad", "Depends on the signal", "More towards the internet network connection from the mobile phone"
		Merchant Limitations with QRIS	"There are still many sellers who do not have QRIS", "Not all can use QRIS", "Not all merchants provide"
		Maximum Payment Limit	"There is still a maximum payment limit"
		Potential Transaction Errors	"Can be used to cheat", "Transactions can be falsified", "If it is not automatic, there is a potential for nominal payment errors", "Misuse", "I often find the EDC machine on the seller's side is in error"
		Underbalance	"The balance is less"
		Neutral/None/No	"-", "None", "Not yet"
12	Suggestions or feedback for the development and performance improvement of QRIS payments	Elimination of Admin Fees	"No admin fee regulation"
		Flexibility and Accessibility	"More flexibility", "QRIS that can be transacted without a data signal"
		Education and Socialization	"Can continue to do massive education", "Socialization in the community"
		Increased Security	"More security is ensured", "Given double verification with pin and fingerprint", "Security is more tightened"
		Increased Maximum Payment Limit	"The maximum payment is further improved"
		Ease of Transaction	"Hope QRIS can be used in transactions on public transportation", "It would be better if merchants only need to scan our QR", "Merchants can produce 1 to 1 barcode so it's easier", "It's better to use automatic ones only"
		Improved Speed and Reliability	"To be more reliable and not detrimental to the seller and buyer", "Security and speed are further improved"

Number	Inquiry	Thematic Unit	Typical Responses
		International Expansion and Acceptance	"QRIS cross border", "So that acceptance is wider at overseas merchants"
		Increased Reach for MSMEs	"Expected to reach MSMEs as much as possible", "Pick up the ball to MSMEs"
		Neutral/None/Not yet	"-", "None", "It's good"

From the analysis, the data collected and analyzed had an impact on the respondents, where they provided some suggestions or input to stakeholders, including industry and regulators, for the improvement of the QRIS system in the future, as follows:

1. 17.31% suggested improvements in terms of security.
2. 13.46% emphasized the need for increased flexibility and accessibility.
3. 13.46% suggested increased socialization, education, and regulation so that digitalization reaches SMEs in all areas.
4. 11.54% suggested increasing the wider reach of QRIS to the MSME sector.
5. 9.62% provided input so that transactions using QRIS are made easier.
6. 5.77% want the admin fee to be eliminated, then to increase the speed and reliability of the QRIS network and system, and to expand QRIS to other countries.
7. 3.85% of respondents expect that in the future, the QRIS system can increase the maximum payment limit.
8. The remaining 13.46% of responses consider QRIS good enough to be used as a daily payment method.

Discussion

In this discussion, key emerging findings show that the Quick Response Code Indonesian Standard (QRIS) is not only widely accepted by consumers but also plays a significant role in changing payment behavior in Indonesia. The use of QRIS, which is praised for its usability and ease of use, reflects a shift in consumer behavior towards more digital and efficient payment methods. However, it is important to highlight that despite the positive reception, some respondents expressed concerns regarding network stability and system security. This indicates that there is ample room for improvement, especially in terms of technology and infrastructure.

Furthermore, these findings indicate that the adoption of digital payment technologies such as QRIS is not only influenced by technological factors alone but also by consumer perceptions and trust in the system. This opens up opportunities for stakeholders to not only focus on technical improvements but also on raising awareness and educating consumers on the benefits and safety of using QRIS. Comparison of the results of this study with previous research:

1. Usability:
   Our research found that usability is an important factor in QRIS acceptance. This result is consistent with the research conducted by Sofwatunnisa et al. (2023), who also highlighted that the ease of use of QRIS increases user satisfaction. Research by de Luna et al. (2019) on mobile payment adoption showed that technology usability significantly affects user adoption, which is in line with our findings.
2. Ease of Use:
   Our finding that ease of use affects QRIS acceptance is in line with the Technology Acceptance Model (TAM) developed by Davis (1989), which states that perceived ease of use is a key determinant in technology acceptance. Research by Khando et al. (2023) also found that ease of use is a major factor in the adoption of digital payment methods, supporting our results.
3. Trust:
   Trust proved to be a critical factor in our study, which is also supported by the research of Gefen et al. (2003), who emphasized the importance of trust in the adoption of online payment

technologies. Research by Tenggino & Mauritsius (2022), shows that trust in transaction security is a determining factor in QRIS usage, which is consistent with our findings.

Additionally, the feedback provided by respondents offers valuable insights in terms of what consumers consider important. Most emphasized is the importance of improving the security, flexibility, and accessibility of the system. This shows that today's consumers are not only looking for convenience but also security in their transactions. Hence, there needs to be a continuous effort to strengthen these aspects of the QRIS system in order to maintain and increase consumer confidence. Some recommendations that can be followed up regarding the factors that influence the acceptance of QRIS by consumers in order to increase trust in using QRIS and increase security in QRIS, such as:

1. Increase User Trust:
   To increase user confidence in using QRIS, service providers can increase transparency regarding security and privacy policies. Communicating the security measures that have been taken to protect user data can help increase trust. Service providers can also provide additional security guarantees, such as two-factor authentication (2FA) and end-to-end encryption, to ensure that user transactions are safe from potential threats.
2. Improving QRIS Security:
   Implement stronger security protocols to protect user data from cyberattacks. This includes using more advanced encryption algorithms and regularly conducting security audits. Conducting educational programs for users on cybersecurity practices, such as the importance of keeping PINs private and avoiding public Wi-Fi networks when making transactions.
3. Improving Ease of Use:
   Service providers can continue to develop user interfaces that are intuitive and easy to use. Providing clear usage guides and responsive customer support can also help users adopt new technologies. Reducing unnecessary steps in the payment process can improve efficiency and user convenience.

Taking all these aspects into consideration, this discussion underlines the importance of QRIS as an innovative payment tool that has great potential for supporting the growth of the digital economy in Indonesia. However, further research is needed to identify specific ways to optimize the QRIS system, especially in the broader context of the digital economy and financial inclusion. In addition, understanding the user experience and addressing the challenges they face can help increase QRIS adoption. Cooperation between financial institutions, regulators, and technology providers is essential to improving the functionality and security of the system. In this way, QRIS can be more effective in facilitating smooth digital transactions and promoting economic development.

Conclusion

This study reveals that factors such as usability, ease of use, and trust have a significant influence on the acceptance of QRIS by consumers, with the majority of respondents giving positive responses. This shows that QRIS, as a digital payment method, successfully meets consumer needs in these aspects. QRIS adoption has also influenced consumer purchasing behavior, with convenience and efficiency being the main factors in choosing this payment method. However, challenges such as network dependency and the stability of the QRIS system remain a concern for consumers.

Implications

This research makes several contributions, both theoretically and practically. From a theoretical perspective, this study contributes to providing a deeper understanding of the factors that influence QRIS adoption, such as ease of use, trust, and usability. This study provides a theoretical framework that illustrates the changes in consumer behavior due to the use of digital payment methods, specifically QRIS. In addition, this study presents an evaluation model that is useful for measuring the impact of QRIS implementation on its general usage.

From a practical perspective, this research contributes by providing practical guidance for the government and other stakeholders to address challenges such as security, network limitations, and consumer education. Also, encouraging accessibility to increase the reach and adoption of QRIS,

especially for MSMEs, helps identify strategic measures for more effective implementation. The study also emphasizes recommendations to improve transaction security and system stability, encouraging user confidence, which is important for the continued use of QRIS.

These contributions demonstrate the importance of QRIS in Indonesia's digital payment ecosystem and how researchers and policymakers can utilize it for further development. By harnessing the potential of QRIS, stakeholders can drive innovation and expand financial inclusion across Indonesia. Ongoing evaluation and feedback from users will be critical to improving the system and addressing emerging challenges. This collaborative approach will ensure QRIS remains a powerful and flexible tool for supporting economic growth and strengthening the digital economy.

Limitations and Future Work

Although this study provides valuable insights into how factors such as usability, ease of use, and trust have a significant influence on consumer acceptance of QRIS, it does have some limitations. This research may only focus on certain regions in Indonesia, so the results may be less representative of the national population. Future research can expand the coverage area to be more representative of the research results. In addition, this study only focused on a relatively small group of respondents (e.g., urban businesses or consumers), so the results may not reflect the experiences of various other user groups, such as those living in rural areas. Future research could expand the role of the respondents or the industries represented to ensure that the findings are more generalizable to the population of respondents studied. In addition, this research process only involved qualitative methods. Future research is expected to use quantitative methods to complement and validate the findings in this study. In addition, the variables studied can also be applied to social and cultural factors. Given the rapid and dynamic changes in payment technology, the results of this study require continuous updating over time in order to remain relevant to the latest developments.

References

Au, Y. A., & Kauffman, R. J. (2008). The economics of mobile payments: Understanding stakeholder issues for an emerging financial technology application. *Electronic Commerce Research and Applications*, *7*(2), 141–164.

Dai, J., Miedema, J., Hernandez, S., Sutton-Lalani, A., & Moffatt, K. (2023). Cognitive Accessibility of Digital Payments: A Literature Review. *ACM International Conference Proceeding Series*, 116 – 121.

Dananjayan, M. P., Gopakumar, S., & Narayanasamy, P. (2023). Money in the age of bits and bytes: Technology in reshaping finance. *Journal of Information Technology Teaching Cases*.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319.

de Luna, I. R., Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2019). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. *Technological Forecasting and Social Change*, *146*, 931–944.

De, P., Dey, K., Mankar, V., & Mukherjea, S. (2015). An Assessment of QR Code as a User Interface Enabler for Mobile Payment Apps on Smartphones. *ACM International Conference Proceeding Series*, *17-19-Dece*, 81 – 84.

Gefen, Karahanna, & Straub. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51.

Jannah, F. Z. (2023). *Kejahatan Keuangan Dalam Pembayaran Digital*. Bank Indonesia. https://www.bi.go.id/id/bi-institute/BI-Epsilon/Pages/Kejahatan-Keuangan-Dalam-Pembayaran-Digital.aspx

Khando, K., Islam, M. S., & Gao, S. (2023). The Emerging Technologies of Digital Payments and Associated Challenges: A Systematic Literature Review. *Future Internet*, *15*(1).

Klepek, M., & Bauerová, R. (2020). Why do Retail Customers Hesitate for Shopping Grocery Online? *Technological and Economic Development of Economy*, *26*(6), 1444–1462.

Liébana-Cabanillas, F., de Luna, I., & Montoro-Ríos, F. J. (2015). User behaviour in QR mobile payment system: the QR Payment Acceptance Model. *Technology Analysis and Strategic Management*, *27*(9), 1031 – 1049.

Lutfi, A., Al-Okaily, M., Alshirah, M. H., Alshira'h, A. F., Abutaber, T. A., & Almarashdah, M. A. (2021). Digital financial inclusion sustainability in Jordanian context. *Sustainability (Switzerland)*, *13*(11).

Malinka, K., Hujňák, O., Hanáček, P., & Hellebrandt, Luk. (2022). E-Banking Security Study—10 Years Later. *IEEE Access*, *10*, 16681–16699.

Mansour, H. (2022). How successful countries are in promoting digital transactions during COVID-19. *Journal of Economic Studies*, *49*(3), 435 – 452.

Mbaidin, H. O., Alsmairat, M. A. K., & Al-Adaileh, R. (2023). Blockchain adoption for sustainable development in developing countries: Challenges and opportunities in the banking sector. *International Journal of Information Management Data Insights*, *3*(2).

Miglionico, A. (2023). Digital payments system and market disruption. *Law and Financial Markets Review*, *0*(0), 1–16.

Rafferty, N. E., & Fajar, A. N. (2022). Integrated QR Payment System (QRIS): Cashless Payment Solution in Developing Country from Merchant Perspective. *Asia Pacific Journal of Information Systems*, *32*(3), 630 – 655.

Rosmayanti. (2021). *Tren Pembayaran Digital di Indonesia 2021: E-Wallet Tumbuh Pesat Hingga 400% Akibat Pandemi*. Warta Ekonomi. https://wartaekonomi.co.id/read381496/tren-pembayaran-digital-di-indonesia-2021-e-wallet-tumbuh-pesat-hingga-400-akibat-pandemi

Simatele, M., & Mbedzi, E. (2021). Consumer payment choices, costs, and risks: Evidence from Zimbabwe. *Cogent Economics \& Finance*, *9*(1), 1875564.

Sofwatunnisa, A. A., Kartawinata, B. R., Akbar, A., & Pradana, M. (2023). Quick Response Code As A Game-Changer of Indonesian Digital Transactions. *WSEAS Transactions on Computer Research*, *11*, 479 – 485.

Stefanelli, V., & Manta, F. (2023). Digital Financial Services and Open Banking Innovation: Are Banks Becoming "invisible"? *Global Business Review*.

Tenggino, D., & Mauritsius, T. (2022). EVALUATION OF FACTORS AFFECTING INTENTION TO USE QRIS PAYMENT TRANSACTION. *ICIC Express Letters*, *16*(4), 343 – 349.

Wicaksono, S. R. (2022). *Teori Dasar Technology Acceptance Model* (1st ed.). CV. Seribu Bintang.

Yamaoka, H. (2023). The Future of Central Banking. *Accounting, Economics and Law: A Convivium*, *13*(2), 103 – 132.

Yi Hu Wu, L. B., & Chen, X. (2023). How does the development of fintech affect financial efficiency? Evidence from China. *Economic Research-Ekonomska Istraživanja*, *36*(2), 2106278.

Yunping Hao, B. Z., & Yin, H. (2023). Can digital finance drive urban–rural integration? *Economic Research-Ekonomska Istraživanja*, *36*(2), 2169736.

Zhong, Y., & Moon, H.-C. (2022). Investigating Customer Behavior of Using Contactless Payment in China: A Comparative Study of Facial Recognition Payment and Mobile QR-Code Payment. *Sustainability (Switzerland)*, *14*(12).

Zilnieks, V. (2020). Concept of a Regulatory Compliant Blockchain Based Instant Payment System. Limitations and Compromises. In G. J., R. A., & K. G. (Eds.), *2020 61st International Scientific Conference on Information Technology and Management Science of Riga Technical University, ITMS 2020 - Proceedings*. Institute of Electrical and Electronics Engineers Inc.

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Examining Students' Continuance Intention in Using AI-Chatbot for Academic Assignment

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Abstract

This research aims to investigate the intention of university students in Indonesia to continue using AI chatbot in doing academic assignments. This research modifies the Post-Acceptance of Information System Continuance model with the ECT (Expectation Confirmation Theory) and TAM (Technology Acceptance Model) as constructs to determine what motivate students to continue using the emerging AI chatbot, namely BING. This study conducted data analysis using Partial Least Squares-Structural Equation Modelling (PLS-SEM). Data are collected through an online survey with 185 respondents who met the inclusion criteria and were used for further analysis. The findings revealed a positive and substantial correlation between Perceived Information Quality (PEIQ), Confirmation (CON), Perceived Usefulness (PEU), Perceived Enjoyment (PEE), Satisfaction (SAT), and Continuance Intention (COI). Confirmation (CON) has a significant impact on how usefulness and enjoyment are perceived, which influences Satisfaction (SAT) and Continuance Intention (COI) to use AI-Chatbot. Meanwhile, Confirmation (CON) and Perceived Ease of Use (PEEOU) have no clear correlation with Satisfaction (SAT). As theoretical contributions, this research provides empirical examination on how those variables influence students' intention to continue using AI chatbots to help them complete academic tasks. Practically for AI Chatbot developers, this research provides information based on user perception to improve the quality of their product. This result also provides insight for university to help design effective strategies to support learning.

Keywords: Chatbot, Expectation Confirmation Theory, Continuance usage intention, Technology Acceptance Model, Perceived Enjoyment, Perceived Ease of Use, Perceived Usefulness

Introduction

The internet has become increasingly integrated into daily life due to the fast access to a wealth of information made possible by its widespread use (Maeda-Minami et al., 2023). In line with technological advances, search engines have evolved into increasingly intelligent search engines supported by

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artificial intelligence (AI). An AI chatbot is a system or computer program used to support and interact with humans through conversation. When humans ask questions, AI chatbot can provide answers or relevant information (Rese & Tränkner, 2023). An AI chatbot aims to facilitate conversational engagements with users by offering responses, information, and support based on pre-established algorithms, machine learning models, or large data sets (Traymbak et al., 2024).

One of AI chatbot currently emerging on the market is BING from Microsoft. BING chatbot is an AI-powered search engine chatbot that offers responses together with user information and a written source (Microsoft, 2023). BING combines AI features with search engine functionality to provide users with a more customized and engaged search experience. BING helps users find relevant information from across the web, information for research data, or inspiration for creativity (Microsoft, 2023). Microsoft launched significant changes to BING including chatbot features based on OpenAI's GPT-4 model (Peters, 2023). Currently, Microsoft changed the status of BING from restricted to open but remains available only in the Edge browser or Microsoft's BING mobile apps (Branscombe, 2023). Therefore, popularity of BING has increased with accesses from one hundred million active users daily (Mehdi, 2023).

In education, AI chatbot, including BING, have various benefits, including enhancing learning, providing personalized support, and increasing educational accessibility (Labadze et al., 2023). Previous research states that students like using AI chatbot because it helps by answering questions and providing explanations that are easy to understand (Neo et al., 2022; Ghayoomi, 2023). This study investigates whether students want to continue using AI chatbot, considering that many students have previously embraced the use of technology to aid with their academic work. This research examines students' continuance intention to use BING because it is allowing users to get current information from the search engine results to help them completing their academic works.

Previous research by Neo et al. (2022) focused on assessing how students feel about using AI chatbots for online instruction and how successful they are at enhancing student learning results. Previous research (Strzelecki, 2024) examines acceptance of ChatGPT from university students in Poland using UTAUT2 model but did not explore the continuance intention to use this technology. Research by (Al-Sharafi et al., 2023) combined constructs from expectation confirmation theory and knowledge management to examine factors influence university students to continue using chatbots for learning. The study found that knowledge applications, perceived usefulness, and information acquisition were critical elements affecting the behavior of students while utilizing chatbots. Other studies (Pasupuleti & Thiyyagura, 2024; Shah et al., 2024) investigated intention of students in India to continue using ChatGPT in academic settings. Both studies utilized constructs from Technology Continuance Theory as determinants. These findings suggest more study into the use of AI chatbots in educational settings. As a result, the current study examines additional factors that impact university students' continued intention to utilize AI chatbots, particularly BING, using empirical information from research models and different countries. The research focuses on Indonesia, which has the fourth-largest population and a lot of potential users for AI chatbots.

This study applies a modified version of the Post-Acceptance of IS Continuance model to clarify why users intend to continue using the BING chatbot. The model is combined with TAM (Technology Acceptance Model) and ECT (Expectation-Confirmation Theory). The ECT model elucidates how user expectations and validation of the initial user experience impact users' Satisfaction (SAT) and Continuance Intention (COI) technology going forward (Oliver, 1980). TAM was used to investigate user Satisfaction (SAT) and Continuance Intention (COI) in the BING chatbot by Perceived Usefulness (PEU) and Perceived Ease of Use (PEEOU) (Davis, 1989). Another variable employed in this study is perceived usability, which assesses user impressions of the BING chatbot and identifies characteristics linked with user Satisfaction (SAT) and Continuance usage (Bevan et al., 2016). Perceived Usefulness (PEU), Perceived Ease of Use (PEEOU), and Perceived Enjoyment (PEE) are the three components of usability that influence user Satisfaction (SAT) and desire to continue using information systems. In addition, this study investigates how the quality of information (PEIQ), as a measure of AI chatbot performance Dwivedi et al. (2012), influences the likelihood to continue using it. The quality of information generated by AI chatbots is critical for students to do correctly in their academic assignments.

This research contributes theoretically to provide insight on how these research variables influence students' intention to continue using new technologies, such as AI chatbots. This research provides practical contributions for BING chatbot developers and educational institutions. For developers, it is needed because AI chatbot technology is relatively new and requires information based on user perceptions to improve the quality of their chatbots. Meanwhile, for educational institutions, it can help design effective strategies to support learning.

Literature Review

Post-Acceptance of IS Continuance

Information system (IS) continuance decisions are like consumer repurchase decisions; they follow the same sequence: the decision to use or purchase a product or service, the experience of using that product or service, and the decision to continue or cancel the original decision (Bhattacherjee, 2001). User satisfaction and perceived post-acceptance usefulness influence users' intentions to continue using. User satisfaction results from perceived usability and validation of expectations from previous use. Perceived usefulness is also influenced by confirmation (Oghuma et al., 2016). Post-Acceptance of IS Continuance is a model that is the focus of Continuance Intention (COI) to use information systems (Inan et al., 2023). Expectation-Confirmation Theory (ECT) is the basis of this model.

Expectation-Confirmation Theory (ECT)

ECT is used to understand why individuals continue using the product. This theory states that product use is influenced by Confirmation (CON) of the user's initial expectations of the product (Ambalov, 2021a). The user's decision to continue using a product or service is based on the extent to which the initial use meets the user's initial expectations (Oliver, 1980). Users who feel a product or service is valuable and satisfying will continue using it (Saxena & Doleck, 2023). User satisfaction is influenced by the confirmation or disconfirmation of their expectations before purchase (Inan et al., 2023). This means that to achieve the repurchase goal, customers follow a sequence of processes. This process starts before the purchase, where they create initial expectations about the product or service. After using the product or service for the first time, they make perceptions about the product or service's performance and compare them with their initial expectations Oghuma et al. (2016).

Technology Acceptance Model (TAM)

TAM is perceived as the usability of determining the Continuance Intention (COI) of information systems. Perceived Usefulness (PEU) and Perceived Ease of Use (PEEOU) from TAM are the main factors that influence Satisfaction (SAT), which ultimately leads to Continuance Intention (COI) using information systems (Inan et al., 2023). TAM as perceived usability can determine the level of user satisfaction and user intention to continue using the information system Oghuma et al. (2016). Perceived usability will be high if the product meets or exceeds user expectations. Conversely, perceived usability will be low if the product does not meet user expectations (Bevan et al., 2016). According to Bhattacherjee (2001), perceived usability is the extent to which users believe using an information system will improve their job performance. Perceived Usefulness (PEU) is the main factor influencing user Satisfaction (SAT) after receiving an information system. In the context of chatbots, Perceived Ease of Use (PEEOU) refers to the extent to which a chatbot can achieve a desired result quickly and efficiently. A technology tends to be more valuable if it is easier to use, as it can save users time and effort (Goli et al., 2023). The perceived usability construct consists of three dimensions, namely Perceived Usefulness (PEU), Perceived Ease of Use (PEEOU), and Perceived Enjoyment (PEE).

This study enhanced previous research model from (Inan et al., 2023). Six significant variables in prior research were included in this study, consist of Confirmation (CON), Satisfaction (SAT), Perceived Usefulness (PEU), Perceived Ease of Use (PEEOU), Perceived Enjoyment (PEE), and Continuance Intention (COI). Performance factors which measured through effectiveness, efficiency, and certainty, have been replaced by Perceived Information Quality (PEIQ) since these three factors have no visible impact on Satisfaction (SAT). We employ Perceived Information Quality (PEIQ) to determine if BING

chatbot users share the same viewpoint as previous research (Jo & Bang, 2023; Khan & Saleh, 2023; Y. Liu et al., 2023; Nie et al., 2023; Nilapun & Jensuttiwetchakul, 2023). Moreover, a previous study by Dwivedi et al. (2012) states that one of the performance components to see user expectations is the Perceived Information Quality (PEIQ). Figure 1 describes how those variables correlate each other in the proposed conceptual model.

Perceived Information Quality (PEIQ) is how information produced by information systems meets user needs (Jo & Bang, 2023). Information quality will support informed decision-making and user Satisfaction (SAT) (Goli et al., 2023). The ability of information systems to provide information that meets user needs, namely clear, accurate, timely, and complete (Niu & Mvondo, 2023). If the sensed information quality matches or exceeds user expectations, the level of Confirmation (CON) and Satisfaction (SAT) will be higher (Staples et al., 2002). Previous studies also revealed that Confirmation (CON) and Satisfaction (SAT) are impacted by Perceived Information Quality (PEIQ) (Jo & Bang, 2023; Khan & Saleh, 2023; Y. Liu et al., 2023; Nie et al., 2023; Nilapun & Jensuttiwetchakul, 2023). However, prior studies indicate that Satisfaction (SAT) is not impacted by Perceived Information Quality (PEIQ) (Carissa et al., 2023). These explanations are used to support the following hypotheses.

H1. Perceived Information Quality (PEIQ) has a significant impact on Confirmation (CON)

H2. Perceived Information Quality (PEIQ) has a significant impact on Satisfaction (SAT)

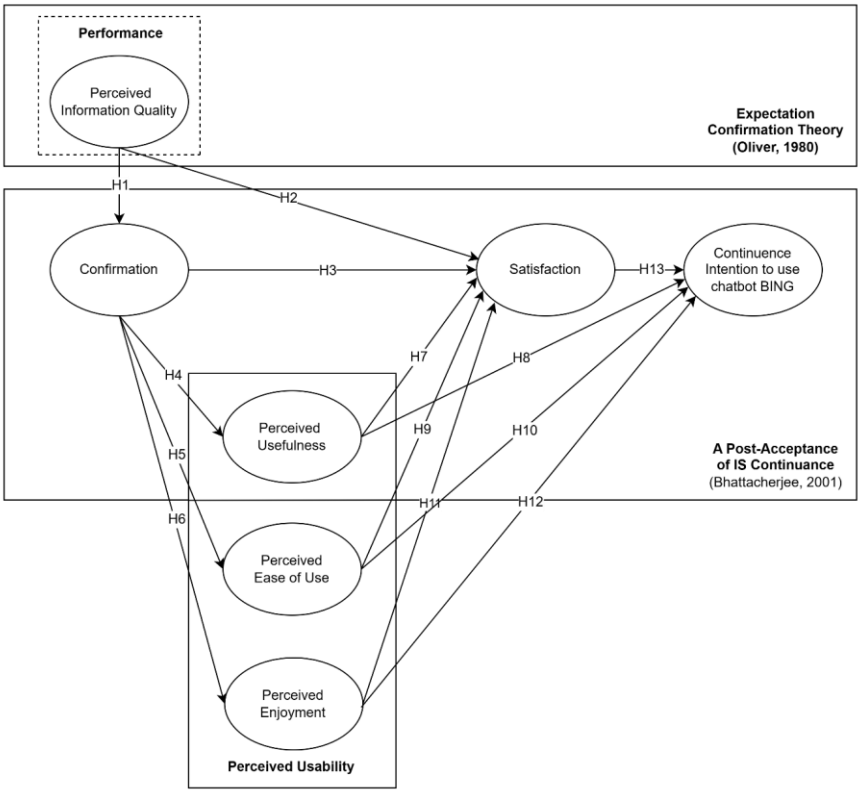

Figure 1. Proposed Conceptual Model

Confirmation (CON) is the conformity between user expectations and information system performance. Disconfirmation is a mismatch between user expectations and information system performance. These two concepts can affect user Satisfaction (SAT) with information systems (Basu et al., 2024). This notion determines how healthy users' expectations are fulfilled when interacting with the BING chatbot in context (Bhattacherjee, 2001). Satisfaction (SAT), Perceived Usefulness (PEU), Perceived Ease of Use (PEEOU), and Perceived Enjoyment (PEE) are impacted by Confirmation (CON) (Inan et al., 2023; Nie et al., 2023; Nilapun & Jensuttiwetchakul, 2023; Oghuma et al., 2016). According to this explanation, we utilize the following hypothesis.

H3. Confirmation (CON) has a significant impact on Satisfaction (SAT).

H4. Confirmation (CON) has a significant impact on Perceived Usefulness (PEU).

H5. Confirmation (CON) has a significant impact on Perceived Ease of Use (PEEOU).

H6. Confirmation (CON) has a significant impact on Perceived Enjoyment (PEE).

Perceived Usefulness (PEU) measures how well a BING chatbot influences user decisions and improves work productivity (Meng & Li, 2023). This is because the usefulness of information systems is the most critical factor in influencing users' intention to continue using information systems (Ambalov, 2021). Satisfaction (SAT) and Continuance Intention (COI) are impacted by Perceived Usefulness (PEU) (Jo & Bang, 2023; Meng & Li, 2023; Oghuma et al., 2016; Roslan et al., 2023). Research Inan et al. (2023) states that Perceived Usefulness (PEU) does not significantly affect Satisfaction (SAT). Therefore, we use the following hypothesis.

H7. Perceived Usefulness (PEU) has significant impact on Satisfaction (SAT)

H8. Perceived Usefulness (PEU) has significant impact on Continuance Intention (COI).

According to Davis (1989), Perceived Ease of Use (PEEOU) is the level of a person believing that using information system technology is easy and does not require hard effort from its users. A few outcomes, such as overall Satisfaction (SAT), the likelihood of recommending information systems to others, and the desire to continue using them, are significantly impacted by Perceived Ease of Use (PEEOU) (Lewis & Sauro, 2023). Satisfaction (SAT) and Continuance Intention (COI) are impacted by Perceived Ease of Use (PEEOU) (Alshurideh et al., 2020; Beldad & Hegner, 2018; Jia et al., 2023; Thong et al., 2006). Prior research has shown that, while Perceived Ease of Use (PEEOU) has not impacted Continuance Intention (COI), it does have an impact on their level of Satisfaction (SAT) (Inan et al., 2023). Based on the explanation, the following hypothesis is used:

H9. Perceived Ease of Use (PEEOU) has a significant impact on Satisfaction (SAT).

H10. Perceived Ease of Use (PEEOU) has a significant impact on Continuance Intention (COI).

Perceived Enjoyment (PEE) is an individual's perception of a system that can provide pleasure and satisfaction in addition to its benefits. Perceived Enjoyment (PEE) considers how well a system works and how enjoyable the experience of using the system is (Jo & Baek, 2023). BING chatbot developers can gain essential insights from Perceived Enjoyment (PEE), an important indicator of users' experience with the BING chatbot they use (Caroux, 2023). Satisfaction (SAT) and Continuance Intention (COI) are impacted by Perceived Enjoyment (PEE) (Liu & Huang, 2023; Lu et al., 2017; Meena & Sarabhai, 2023; Mishra et al., 2023). Based on the explanation, the following hypothesis is used:

H11. Perceived Enjoyment (PEE) has a significant impact on Satisfaction (SAT).

H12. Perceived Enjoyment (PEE) has a significant impact on Continuance Intention (COI).

Satisfaction (SAT) is the user's positive perception of the performance of the information system in meeting their needs and expectations (Lee et al., 2023). The primary factor influencing students' motivation to continue using BING chatbots is Satisfaction (SAT) (Khurshed & Aljader, 2023). According to the research, Continuance Intention (COI) is impacted by Satisfaction (SAT) (Inan et al., 2023; Lee et al., 2023; Mao et al., 2023; Meng & Li, 2023; Oghuma et al., 2016). Based on the explanation, the following hypothesis is used:

H13. Satisfaction (SAT) has a significant impact on Continuance Intention (COI).

Methodology

This research uses quantitative methods. The research steps include problem identification, collection of theories and previous research, develop research framework and hypotheses, data collection, validity and reliability tests, data analysis, and drawing conclusions and recommendations. In the problem identification processes, we discover problems from media reports and prior research that describe new technologies, such as chatbot that employ artificial intelligence and are in high demand among students.

Next, a framework and theory are created and used to answer the research problem, the truth of which must be verified empirically based on previous research findings and then developed.

This study uses PLS-SEM (Partial Least Square-Structural Equation Modeling) as a data analysis technique. PLS-SEM was used because of its flexibility for small sample sizes, ability to manage complex models, ease of interpretation of results, and ability to handle formative and reflective constructs (Hair et al., 2021). The measurement model or outer model shows goodness of measurement through reliability tests, convergent, and discriminant. Meanwhile, the inner model or structural model shows the hypotheses testing result through path coefficient value.

The population of this research is university students in Indonesia who have used the BING chatbot for more than three months. By giving the timeframe, we expect that they can objectively assess it by recalling their experience while using the BING chatbot (Indrawati et al., 2021). This study used purposive sampling (Campbell et al., 2020) with minimum sampling size calculated by ten times to maximum number of arrows pointing to latent variables in the PLS path model (Hair et al., 2021). This study has 13 paths; thus, the minimum sample is 130 respondents.

We developed a research instrument adopting indicators from (Inan et al., 2023) for six variables (CON, PEE, PEEOU, PEU, SAT, and COI). We modified the items in the questionnaire from group discussion context into BING usage for academic assignment. Meanwhile, the items for variable PEIQ were adopted from Dwivedi et al. (2012) and adjusted to this research context. The data is collected using questionnaires in Google Forms that are distributed through social media networks. We use 5-Likert scale, ranging from 1 (one) strongly disagree to 5 (five) strongly agree, to score the respondents' responses.

Results

Socio-Demographic Characteristics of Respondents

Data collected from the survey are 227, but only 185 were used for further analysis because 42 respondents did not meet the criteria, namely active students in Indonesia and users of the BING chatbot for more than 3 months. Table 1 displays the information about respondents' characteristics.

Table 1. Respondent's Demographic Characteristics

Profile	Category	Frequency	Percentage
Gender	Male	95	51.35%
	Female	90	48.65%
Age	18 - 24 years	150	81.08%
	25 - 34 years	24	12.97%
	>35	11	5.95%
Education Level	Diploma	41	22.16%
	Undergraduate	103	55.68%
	Graduate & Postgraduate	41	22.16%
Using Frequency	Very Rarely (4 weeks at least 1x)	58	31.35%
	Rarely (3 weeks at least 1x)	67	36.22%
	Frequently (2 weeks at least 1x)	40	21.62%
	Very Often (1 week at least 1x)	20	10.81%

Validity and Reliability Test

CA (Cronbach's Alpha) and CR (Composite Reliability) demonstrate reliability. Convergent can be seen from AVE (Average Variance Extracted) and FL (Factor Loading). Acceptable factor loadings if the values are > 0.70, while AVE is acceptable provided the value is >0.50 (Hair et al., 2021). The Fornell-Larcker Criterion indicates the discriminant validity. If the square shape of a construct's AVE is greater than the square root of the construct with the highest correlation, the construct is considered valid (Hair et al., 2021). If the variable value is more significant than >0.70, composite reliability can be accepted, and if the variable value is more significant than 0.70, Cronbach's Alpha can be accepted (Hair et al., 2021).

Table 2 shows that each construct satisfies the prerequisites, namely FL (Factor Loading) >0.7, and is therefore considered valid. Then, each variable is deemed valid since its AVE (Average Variance Extracted) exceeds the criterion of >0.50. Table 3 shows that the square shape of AVE for every construct is more significant than the construct with the strongest correlation. Each construct is recognized as legitimate. According to Table 2, all constructs in this study exhibit good reliability and fulfill the requirements, with CA and CR values for each variable or construct more than 0.7.

Table 2. Convergent and Reliability Test

Research Variable	Code	FL	CA	CR	AVE
Perceived Information Quality (PEIQ)	PEIQ1	0.731	0.710	0.711	0.534
	PEIQ2	0.726			
	PEIQ3	0.753			
	PEIQ4	0.713			
Confirmation (CON)	CON1	0.701	0.701	0.701	0.527
	CON2	0.718			
	CON3	0.723			
	CON4	0.761			
Perceived Usefulness (PEU)	PEU1	0.735	0.750	0.750	0.571
	PEU2	0.757			
	PEU3	0.773			
	PEU4	0.758			
Perceived Ease of Use (PEEOU)	PEEOU1	0.782	0.737	0.745	0.555
	PEEOU2	0.737			
	PEEOU3	0.712			
	PEEOU4	0.747			
Perceived Enjoyment (PEE)	PEE1	0.746	0.783	0.785	0.607
	PEE2	0.844			
	PEE3	0.753			
	PEE4	0.769			
Satisfaction (SAT)	SAT1	0.822	0.791	0.797	0.615
	SAT2	0.754			
	SAT3	0.725			
	SAT4	0.832			
Continuing Intention (COI)	COI1	0.818	0.774	0.777	0.597

Research Variable	Code	FL	CA	CR	AVE
	COI2	0.745			
	COI3	0.778			
	COI4	0.747			

Table 3. Discriminant Test

	CON	COI	PEEOU	PEE	PEIQ	PEU	SAT
CON	**0.726**						
COI	0.653	**0.773**					
PEEOU	0.633	0.648	**0.745**				
PEE	0.660	0.771	0.673	**0.779**			
PEIQ	0.703	0.728	0.729	0.723	**0.731**		
PEU	0.695	0.757	0.667	0.724	0.783	**0.756**	
SAT	0.660	0.760	0.671	0.760	0.742	0.756	**0.785**

Data Analysis

Bootstrapping is used in hypothesis testing using a 5,000 subsample and a 5% significance level (Inan et al., 2023). A two-way test with a 5% significance level is used in this investigation. Path coefficients can be classified into two groups based on their proximity to +1, which signifies strong positive relationships, and −1, which indicates strong negative relationships. Relevance is reflected in these ranges (Hair, Hult, et al., 2021). The P-value represents the possibility of getting a conclusion as extreme as or more significant than the actual data if the independent and dependent variables do not correlate. The hypothesis is assumed to be statistically significant if the p-value is under 0.05. (Hair, Hult, et al., 2021). Since the developed hypothesis does not require direction, the measurement uses a two-tail evaluation.

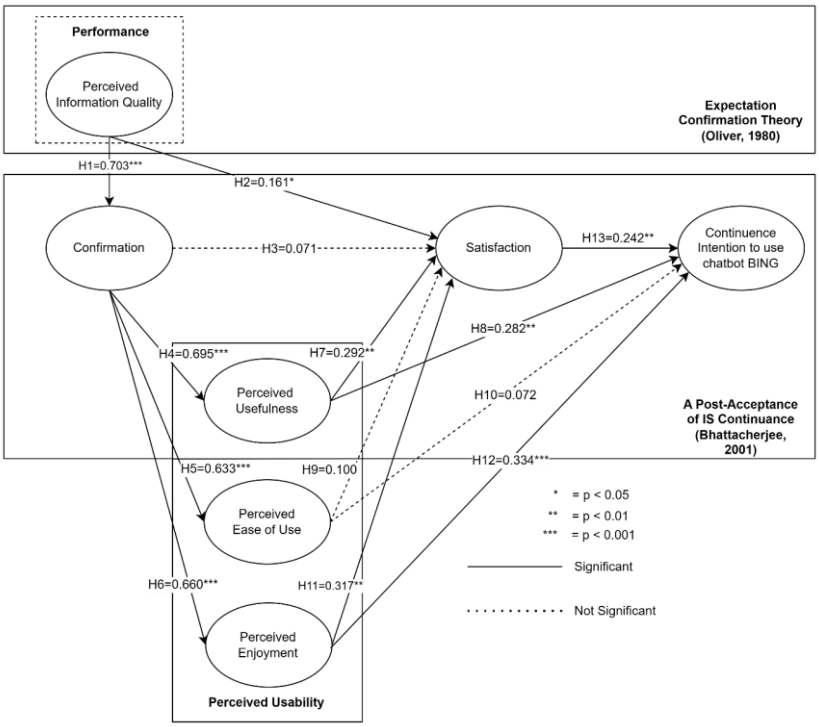

Figure 2. Evaluated Research Model

Figure 2 and Table 4 show that all the hypotheses have positive path coefficient values. The result implies that all accepted hypotheses have a positive correlation between related variables. Every hypothesis suggests that the independent and dependent variables have a unidirectional relationship. Ten of the thirteen hypotheses are accepted based on the hypotheses testing result. However, H3, H9, and H10, are rejected since the p-value are less than 0.05. The hypothesis test results suggest that user willingness to continue using the BING chatbot is highly impacted by Perceived Enjoyment (PEE) with a path value of 0.334. Perceived Usefulness (PEU) is in the second rank with a path value of 0.282, while Satisfaction (SAT) is in the third rank with a path value of 0.242.

Table 4. Hypothesis Testing

Hypothesis	Path Coefficient	T Statistics	P Values	Description
H1: PEIQ → CON	0.703	16.239	0.000	H1 Accepted
H2: PEIQ → SAT	0.161	2.081	0.037	H2 Accepted
H3: CON → SAT	0.071	0.843	0.400	H3 Rejected
H4: CON → PEU	0.695	15.028	0.000	H4 Accepted
H5: CON → PEEOU	0.633	12.686	0.000	H5 Accepted
H6: CON → PEE	0.660	13.889	0.000	H6 Accepted
H7: PEU → SAT	0.292	3.443	0.001	H7 Accepted
H8: PEU → COI	0.282	3.328	0.001	H8 Accepted
H9: PEEOU → SAT	0.100	1.530	0.126	H9 Rejected
H10: PEEOU → COI	0.072	1.015	0.310	H10 Rejected
H11: PEE → SAT	0.317	3.037	0.002	H11 Accepted
H12: PEE →COI	0.334	4.065	0.000	H12 Accepted
H13: SAT → COI	0.242	2.919	0.004	H13 Accepted

By focusing on the statistical significance of these explanatory variables, R-Square is utilized as a metric to gauge how successfully the regression model achieves the study's goals, which include determining how predictor variables affect the dependent variable (Ozili, 2023). If some or most predictor variables have statistically essential effects on the dependent variable, R-Squared values between 0.10 and 0.99 (or between 10% and 99%) are deemed acceptable (Ozili, 2023). Table 5 demonstrates the determination coefficient value that is acceptable for all variables. Our research findings indicate that Continuance Intention (COI) has a coefficient of determination of 0.494. The determination coefficients for all usability variables are similar, with values of Perceived Enjoyment (0.435), Perceived Usefulness (0.483), and Perceived Ease of Use (0.401). This suggests that Confirmation (CON) is moderately influenced by perceived usability among students using BING. Meanwhile, Satisfaction (SAT) and Confirmation (CON) exhibit higher determination coefficient values of 0.698 and 0.702, respectively. In this study, we only examined Perceived Information Quality (PEIQ) as a determinant of Confirmation (CON) and found it to be a significant measure of AI Chatbot performance.

Table 5. Determination Coefficient

Factor	R-Square
COI	0.494
SAT	0.698
PEE	0.435
PEU	0.483
PEEOU	0.401
CON	0.702

Discussion

These findings validate Bhattacharjee's concerns, who made a distinction between his work and Oliver's about IS Continuance (Inan et al., 2023). This study contradicts previous research that found that Satisfaction (SAT) and Continuance Intention (COI) are impacted by Perceived Ease of Use (PEEOU) (Alshurideh et al., 2020; Beldad & Hegner, 2018; Jia et al., 2023; Thong et al., 2006). Nonetheless, Inan et al. (2023) assert that Continuance Intention (COI) is not impacted by Perceived Ease of Use (PEEOU). It could be happened because students in Indonesia consider ease of use, learning, mastery, and interaction cannot affect their intention to use the technology as represented by Continuance Intention (COI) variable. Moreover, the results are not supported by earlier research, which showed Satisfaction (SAT) is impacted by Confirmation (CON) (Inan et al., 2023; Nie et al., 2023; Nilapun & Jensuttiwetchakul, 2023; Oghuma et al., 2016). This finding is like several previous studies that found Satisfaction (SAT) and Continuance Intention (COI) are impacted by Perceived Enjoyment (PEE) (Liu & Huang, 2023; Lu et al., 2017; Meena & Sarabhai, 2023; Mishra et al., 2023). Students in Indonesia perceive the enjoyment of using tools, the satisfaction derived from completing tasks, the assistance these tools provide, and their practicality as factors influencing their Continuance Intention (COI). Perceived Enjoyment (PEE) encompasses an information system's benefits or functionality and an individual's experience of happiness and contentment from utilizing it (Jo & Baek, 2023). Perceived Enjoyment (PEE) is mediated by Confirmation (CON), which is also mediated by Perceived Information Quality (PEIQ) to impact Continuance Intention (COI) significantly. The second highest factor that affects Continuance Intention (COI) is Perceived Usefulness (PEU). Previous research revealed that Continuance Intention (COI) is impacted by Perceived Usefulness (PEU) (Jo & Bang, 2023; Meng & Li, 2023; Oghuma et al., 2016; Roslan et al., 2023). Students in Indonesia believe that the speed of information, the benefits gained, their needs, and performance improvement can influence their Continuance Intention (COI). Perceived Usefulness (PEU) and Perceived Enjoyment (PEE) are also mediated by Confirmation (CON), which is also influenced by Perceived Information Quality (PEIQ) to impact Continuance Intention (COI) significantly. The third highest factor is Satisfaction (SAT). Prior research has demonstrated that Satisfaction impacts Continuance Intention (COI) (SAT) (Inan et al., 2023; Lee et al., 2023; Mao et al., 2023; Meng & Li, 2023; Oghuma et al., 2016). Students in Indonesia perceive that usage satisfaction, convenience, and the information provided influence their Continuing Intention (COI). User Satisfaction (SAT) is mediated by Perceived Enjoyment (PEE), Perceived Usefulness (PEU), and Perceived Information Quality (PEIQ) to impact Continuance Intention (COI) significantly.

This study aims to find out if Indonesian students will continue using the BING chatbot to help them with their schoolwork. In this study, we implement the Post-Acceptance Model to investigate the BING chatbot's Continuance Intention (COI) (Inan et al., 2023). We believe that the Post-Acceptance Model can determine the Continuance intention on IS. However, Satisfaction (SAT) is not impacted by Confirmation (CON), but Perceived Usefulness (PEU) and Perceived Enjoyment (PEE) will function as mediators to raise Satisfaction (SAT). The findings of this study also show that to find user motivation to continue using information systems not only by using TCT (Nurdin et al., 2023), TAM (Hariguna & Akmal, 2019), and ECM (Oghuma et al., 2016). Combining ECT and post-acceptance models can clarify students' Continuance Intention (COI). This study highlights the importance of Perceived Information Quality (PEIQ) when using the BING chatbot. However, this study has results different from previous studies that used the TAM model to determine student motivation to continue using information systems. Previous research, Continuance Intention, was impacted by Perceived Ease of Use (PEEOU), while this study did not.

As theoretical contribution, these findings suggest that students' continuance usage intention for accomplishing academic works is significantly influenced by their perceived enjoyment, perceived usefulness, and satisfaction. Future research can explore other variables or factors that have the potential to influence users' intention to continue using information systems, such as perceived intelligence (Huang & Yu, 2023). Furthermore, future research should use other respondents in academic environment, such as the lecturer, to get different perspectives and experiences when using AI chatbots (Bettini et al., 2020; Shahzad et al., 2024). Practically, to improve Perceived Information Quality (PEIQ), Confirmation (CON), and Perceived Usefulness (PEU), developers can implement Natural

Language Processing (NLP) technology to improve chatbot performance in understanding user questions and expanding the knowledge base to improve answer accuracy (Jo & Bang, 2023; Saxena & Doleck, 2023). Furthermore, to increase Perceived Enjoyment (PEE) and Satisfaction (SAT), the BING chatbot developer can improve the UI/UX of the BING chatbot. So that users can feel even better comfort and enjoyment (Sundar et al., 2015).

Conclusion

According to the findings, students will continue to be motivated to use the BING chatbot for enjoyment, usefulness, and satisfaction. However, Perceived Ease of Use (PEEOU) does not impact students' desire to continue using the BING chatbot. The study's findings can help developers attract new users and maintain existing ones, particularly by enhancing users' Perceived Enjoyment (PEE). This study solely looks at Perceived Information Quality (PEIQ) about performance. DeLone and McLean define the efficacy of information systems as perceived information quality, service quality, and system quality. We propose further research to include system quality and service quality variables to be investigated. There are several limitations in this study. First, we examined BING chatbot users in one country. Since each country has unique customs and laws, extra caution should be used when extrapolating the study's conclusions. However, we strongly recommend that future research examine BING chatbots in different countries. Secondly, most of respondents were undergraduate students. Due to this situation, we cannot extrapolate the findings to all degree. Thirdly, we limited our research to Indonesian college students who use the BING chatbot. Each career has unique responsibilities and activities. Compared to college students, professionals in other fields may value various attributes. Moreover, they may use other AI chatbot programs. Future studies can examine the usage patterns differences among users of different professional categories.

References

Al-Sharafi, M. A., Al-Emran, M., Iranmanesh, M., Al-Qaysi, N., Iahad, N. A., & Arpaci, I. (2023). Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach. *Interactive Learning Environments*, *31*(10), 7491–7510.

Alshurideh, M., Al Kurdi, B., Salloum, S. A., Arpaci, I., & Al-Emran, M. (2020). Predicting the actual use of m-learning systems: a comparative approach using PLS-SEM and machine learning algorithms. *Interactive Learning Environments*.

Ambalov, I. A. (2021a). An investigation of technology trust and habit in IT use continuance: a study of a social network. *Journal of Systems and Information Technology*, *23*(1), 53–81.

Ambalov, I. A. (2021b). Decomposition of perceived usefulness: A theoretical perspective and empirical test. *Technology in Society*, *64*.

Basu, B., Sebastian, M. P., & Kar, A. K. (2024). What affects the promoting intention of mobile banking services? Insights from mining consumer reviews. *Journal of Retailing and Consumer Services*, *77*.

Beldad, A. D., & Hegner, S. M. (2018). Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue using a Fitness App: A Structural Equation Modeling Approach. *International Journal of Human-Computer Interaction*, *34*(9), 882–893.

Bettini, E., Gilmour, A. F., Williams, T. O., & Billingsley, B. (2020). Predicting Special and General Educators' Intent to Continue Teaching Using Conservation of Resources Theory. *Exceptional Children*, *86*(3), 310–329.

Bevan, N., Carter, J., Earthy, J., Geis, T., & Harker, S. (2016). New ISO standards for usability, usability reports and usability measures. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9731*, 268–278.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model 1 Motivation For The Study. *MIS Quarterly*, *25*(3), 351–370.

Branscombe, M. (2023, May 4). *Bing AI Chat is now open to everyone, though still in preview*. www.techrepublic.com. https://www.techrepublic.com/article/bing-ai-chat-open/

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: complex or simple? Research case examples. *Journal of Research in Nursing*, *25*(8), 652–661.

Carissa, N. E., Erlangga, M., Sonesha Evik, C., & Handayani, P. W. (2023). The Influence of Perceived Usefulness, Satisfaction, and Personalization on Subscription Video on Demand Continuance Intentions. In *CommIT Journal* (Vol. 17, Issue 2).

Caroux, L. (2023). Presence in video games: A systematic review and meta-analysis of the effects of game design choices. In *Applied Ergonomics* (Vol. 107). Elsevier Ltd.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339.

Dwivedi, Y. K., Wade, M. R., & Schneberger, S. L. (2012). *Information Systems Theory Explaining and Predicting Our Digital Society, Vol. 1* (R. Sharda & S. Voß, Eds.; Vol. 28). Springer.

Ghayoomi , H. ., & Partohaghighi , M. . (2023). Investigating lake drought prevention using a DRL-based method. *Engineering Applications*, *2*(1), 49–59.

Goli, M., Sahu, A. K., Bag, S., & Dhamija, P. (2023). Users' Acceptance of Artificial Intelligence-Based Chatbots: An Empirical Study. *International Journal of Technology and Human Interaction*, *19*(1).

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) Third Edition* (3rd ed.). Sage Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Evaluation of the Structural Model. In: Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Classroom Companion: Business*. Springer, Cham.

Hariguna, T., & Akmal, A. (2019). Assessing students' continuance intention in using multimedia online learning. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *17*(1), 187.

Huang, Y., & Yu, Z. (2023). Understanding the Continuance Intention for Artificial Intelligence News Anchor: Based on the Expectation Confirmation Theory. *Systems*, *11*(9), 438.

Inan, D. I., Hidayanto, A. N., Juita, R., Lesmono, D. R., Honggo, F., Melissa, M., & Melianti, S. D. (2023). What Motivate Students to Continue Using Online Collaborative Tools: Post-Acceptance of Information System Approach. *International Journal of Emerging Technologies in Learning*, *18*(9), 49–64.

Indrawati, Khairunnisa, R., & Muthaiyah, S. (2021). Understanding Factors Influencing Continuance Intention Of Users Toward Community-Based Traffic And Navigation Application In Indonesia. *Turkish Journal of Computer and Mathematics*, *12*(12), 3464–3476.

Jia, X., Pang, Y., Huang, B., & Hou, F. (2023). Understanding consumers' continuance intention to watch streams: A value-based continuance intention model. *Frontiers in Psychology*, *14*.

Jo, H., & Baek, E. M. (2023). Customization, loneliness, and optimism: drivers of intelligent personal assistant continuance intention during COVID-19. *Humanities and Social Sciences Communications*, *10*(1).

Jo, H., & Bang, Y. (2023). Understanding continuance intention of enterprise resource planning (ERP): TOE, TAM, and IS success model. *Heliyon*, *9*(10).

Khan, M. I., & Saleh, M. A. (2023). Facebook Users' Satisfaction and Intention to Continue Using It: Applying the Expectation Confirmation Model. *Social Science Computer Review*, *41*(3), 983–1000.

Khurshed, H., & Aljader, S. (2023). Measuring the Effect of E-Learning Information Quality on Student's Satisfaction Using the Technology Acceptance Model. *International Journal on Informatics Visualization*, *7*(3), 878–885.

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: systematic literature review. In *International Journal of Educational Technology in Higher Education* (Vol. 20, Issue 1). Springer Science and Business Media Deutschland GmbH.

Lee, J. C., Tang, Y., & Jiang, S. Q. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model. *Humanities and Social Sciences Communications*, *10*(1).

Lewis, J. R., & Sauro, J. (2023). Effect of Perceived Ease of Use and Usefulness on UX and Behavioral Outcomes. *International Journal of Human-Computer Interaction*.

Liu, C., & Huang, X. (2023). Does the selection of virtual reality video matter? A laboratory experimental study of the influences of arousal. *Journal of Hospitality and Tourism Management*, *54*, 152–165.

Liu, Y., Li, Q., Edu, T., & Negricea, I. C. (2023). Exploring the Continuance Usage Intention of Travel Applications in the Case of Chinese Tourists. *Journal of Hospitality and Tourism Research*, *47*(1), 6–32.

Lu, J., Liu, C., & Wei, J. (2017). How important are enjoyment and mobility for mobile applications? *Journal of Computer Information Systems*, *57*(1), 1–12.

Maeda-Minami, A., Yoshino, T., Yumoto, T., Sato, K., Sagara, A., Inaba, K., Kominato, H., Kimura, T., Takishita, T., Watanabe, G., Nakamura, T., Mano, Y., Horiba, Y., Watanabe, K., & Kamei, J. (2023). Development of a novel drug information provision system for Kampo medicine using natural language processing technology. *BMC Medical Informatics and Decision Making*, *23*(1).

Mao, Z., Zou, Q., Bu, T., Dong, Y., & Yan, R. (2023). Understanding the Role of Service Quality of Government APPs in Continuance Intention: An Expectation–Confirmation Perspective. *SAGE Open*, *13*(4).

Meena, R., & Sarabhai, S. (2023). Extrinsic and intrinsic motivators for usage continuance of hedonic mobile apps. *Journal of Retailing and Consumer Services*, *71*.

Mehdi, Y. (2023, March 8). *The New Bing and Edge – Progress from Our First Month*. Blogs.Bing.Com. https://blogs.bing.com/search/march_2023/The-New-Bing-and-Edge-%E2%80%93-Momentum-from-Our-First-Month/

Meng, Z., & Li, R. (2023). Understanding Chinese teachers' informal online learning continuance in a mobile learning community: an intrinsic–extrinsic motivation perspective. *Journal of Computing in Higher Education*.

Microsoft. (2023, February). *The new Bing: Our approach to Responsible AI*. Www.Microsoft.Com. https://support.microsoft.com/en-us/topic/the-new-bing-our-approach-to-responsible-ai-45b5eae8-7466-43e1-ae98-b48f8ff8fd44

Mishra, A., Shukla, A., Rana, N. P., Currie, W. L., & Dwivedi, Y. K. (2023). Re-examining post-acceptance model of information systems continuance: A revised theoretical model using MASEM approach. *International Journal of Information Management*, *68*.

Neo, M., Lee, C. P., Tan, H. Y. J., Neo, T. K., Tan, Y. X., Mahendru, N., & Ismat, Z. (2022). Enhancing Students' Online Learning Experiences with Artificial Intelligence (AI): The MERLIN Project. *International Journal of Technology*, *13*(5), 1023–1034.

Nie, L., Oldenburg, B., Cao, Y., & Ren, W. (2023). Continuous usage intention of mobile health services: model construction and validation. *BMC Health Services Research*, *23*(1).

Nilapun, M., & Jensuttiwetchakul, T. (2023). The Effect of System Quality, Information Quality, and Service Quality on the Continued Usage of Mobile Payment Application in Thailand. *ACM International Conference Proceeding Series*, 101–108.

Niu, B., & Mvondo, G. F. N. (2023). I Am ChatGPT, the ultimate AI Chatbot! Investigating the determinants of users' loyalty and ethical usage concerns of ChatGPT. *Journal of Retailing and Consumer Services*, *76*, 103562.

Nurdin, N., Pettalongi, S. S., Ahsan, M. N., & Febrianti, V. F. (2023). Factors affecting students' continuance intention to use teaching performance assessment application from technology continuance theory. *International Journal of Electrical and Computer Engineering (IJECE)*, *13*(5), 5342.

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. *Telematics and Informatics*, *33*(1), 34–47.

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, *17*(4), 460–469.

Ozili, P. K. (2023). *The Acceptable R-square in Empirical Modelling for Social Science Research*.

Pasupuleti, R. S., & Thiyyagura, D. (2024). An empirical evidence on the continuance and recommendation intention of ChatGPT among higher education students in India: An extended technology continuance theory. *Education and Information Technologies*.

Peters, J. (2023, March 15). *Microsoft was already using OpenAI's GPT-4 model for the Bing AI chatbot - The Verge*. Www.Theverge.Com. https://www.theverge.com/2023/3/14/23639928/microsoft-bing-chatbot-ai-gpt-4-llm

Rese, A., & Tränkner, P. (2023). Perceived conversational ability of task-based chatbots – Which conversational elements influence the success of text-based dialogues? *International Journal of Information Management*, *74*.

Roslan, R., Ayub, A. F. M., Ghazali, N., Zulkifli, N. N., Latip, S. N. H. M., & Hanifah, S. S. A. (2023). Predictive Model for Factors Influencing Students' Continuance Usage Intention on a Gamified Formative Assessment Application. *Journal of Technical Education and Training*, *15*(3), 12–24.

Saxena, A., & Doleck, T. (2023). A structural model of student continuance intentions in ChatGPT adoption. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(12).

Shah, C. S., Mathur, S., & Vishnoi, S. Kr. (2024). Continuance Intention of ChatGPT Use by Students. In S. K. Sharma, Y. K. Dwivedi, B. Metri, B. Lal, & A. Elbanna (Eds.), *Transfer, Diffusion and Adoption of Next-Generation Digital Technologies* (pp. 159–175). Springer Nature Switzerland.

Shahzad, M. F., Xu, S., & Baheer, R. (2024). Assessing the factors influencing the intention to use information and communication technology implementation and acceptance in China's education sector. *Humanities and Social Sciences Communications*, *11*(1).

Staples, D. S., Wong, I., & Seddon, P. B. (2002). Applications of Chatbots in Education. *Information & Management*, *40*(2), 115–131.

Strzelecki, A. (2024). Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education*, *49*(2), 223–245.

Sundar, S. S., Jia, H., Waddell, T. F., & Huang, Y. (2015). Toward a Theory of Interactive Media Effects (TIME). In *The Handbook of the Psychology of Communication Technology*.

Thong, J. Y. L., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human Computer Studies*, *64*(9), 799–810.

Traymbak, S., Sharma, M., Anand, A., & Shukla, A. (2024). Chatbot technology in the education sector: a bibliometrics analysis using VOS viewer. *International Journal of System Assurance Engineering and Management*.

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Big Data Analytics in Gaza's Higher Education: Identifying and Addressing Key Implementation Barriers

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Abstract

This research provides an in-depth investigation into the adoption of Big Data Analytics (BDA) technology in higher education institutions (HEIs) in the Gaza Strip, along with a detailed analysis of the barriers to its implementation. Using quantitative research methodology, data was collected from 305 participants. Principal Component Analysis (PCA) was employed to identify key barriers to BDA, including challenges related to infrastructure, security, resources, knowledge, and data characteristics. The study found that financial constraints, access pricing and conditions, significant investment costs, lack of BDA expertise, operational expenses, experience sharing, and resource development are the main barriers to BDA adoption. Additionally, the study shows that 65.3% of HEIs are using BDA technology, with a BDA readiness score of 66.68%. Regression analysis indicates that barriers related to security, finances, data characteristics, skills, and infrastructure negatively impact BDA practice and readiness. Based on these findings, proactive measures are recommended to address these barriers in the Gaza Strip. These measures include developing government initiatives, upgrading IT infrastructure, enhancing BDA skills, and promoting BDA technology awareness. The research advocates for further exploration of the specific challenges and opportunities faced by local universities and a deeper investigation into the potential benefits of BDA adoption. Overcoming these obstacles and fostering BDA integration could enhance data analysis capabilities, contributing to the growth and competitive strength of the Gaza Strip.

Keywords: big data, big data analytics, barriers of adaption big data analytics, Gaza strip

Introduction

The widespread adoption of the internet and related technologies such as social networking, cloud computing, e-banking, e-commerce, search engines, and the Internet of Things (IoT) has led to a significant surge in data. Additionally, many businesses rely on information systems and databases to manage a wide range of operations. These systems have evolved to improve interactions between customers and suppliers, strengthening their competitive advantage. This amalgamation of databases has resulted in extensive datasets commonly referred to as "big data" (BD) (Acharjya & Kauser, 2016; Alharthi et al., 2017; Bhadani & Jothimani, 2016; Lutfi et al., 2023; Yousef, 2023). Currently, the digital landscape contains over 44 zettabytes of data, highlighting the vastness of digital information (Statista, 2022). The term "big data" gained significant attention in academia and industry after 2011, driven by rapid advancements in information and communication technology (ICT) (Bedeley, 2014; Li et al., 2015; Lutfi et al., 2022). The business world largely regards Big Data Analytics (BDA) as an asset that facilitates rapid decision-making and significant revenue generation, as emphasized by (Wahab et al., 2021). Despite the early acknowledgment of the strategic importance of BD, the adoption of BDA

technology faces a variety of obstacles spanning hardware, software, policy, skills, and data complexity, as outlined by (Bhadani & Jothimani, 2016; Jeble et al., 2018).

Academic revolutions have occurred over the past 20 years because of advancements in ICT, which are remarkable in their wide-ranging breadth and the stakeholders they impact (Williams, 2016). The pressure on academic institutions to respond to regional, national, and global economic, social, and political change is growing. HEIs have adopted BDA technology with the promise of a variety of benefits, from better decision-making to individualized student experiences (Aseeri & Kang, 2023; Kalim, 2021).

HEIs in Palestine employed a total of 17,477 people during the academic year 2022–2021, including both male and female staff members. This workforce was distributed across various roles, with 7,367 individuals serving as educators, 611 in administrative positions, 16 as researchers, 999 in various administrative roles, 2,632 working as secretaries, 2,162 serving as teaching assistants, 1,072 in professional capacities, and 622 employed as technicians and artisans (PCBS, 2021). Additionally, the Palestinian Ministry of Higher Education and Scientific Research reported 1,996 other employees. Significantly, a substantial portion of these institutions relies heavily on databases, with many of their employees, including academics and administrators, depending on these databases for the efficient and accurate execution of their responsibilities. These databases play a pivotal role in supporting diverse university operations, ensuring smooth functionality, and facilitating well-informed decision-making processes, resulting in the accumulation of extensive volumes of data. According to the research conducted by Nazarenko and Khronusova (2017), the adoption of BDA technology should be considered by prestigious modern universities that prioritize educational quality. This approach enables the enhancement of effective decision-making in education through the integration of various information and communication technologies, as advocated by Kalim (2021). However, the value extracted from this data remains largely untapped, with current studies indicating that only a mere 0.05% of this data has undergone analysis (Barakat, 2016). This study aims to address the following questions to identify the factors hindering the realization of BD's potential in the HEIs of the Gaza Strip.

RQ1: What is the extent of BDA technology adoption within the HEIs?

RQ2: What are the barriers hindering the implementation of BDA in HEIs?

RQ3: To what extent is the HEIs ready to adopt BDA technology?

RQ4: How do BDA barriers affect BDA technology adoption in HEIs?

Literature Review

Understanding Big Data (BD)

The rapid strides made in ICT and the widespread adoption of social media have propelled the emergence of the concept known as BD. Initially defined by Roger Magoulas as a repository of extensive and intricate data (Ularu et al., (2012)), BD has engendered diverse interpretations within the scholarly realm. As proposed by Acharjya and Kauser (2016) and Balachandran and Prasad (2017), BD comprises extensive and intricate datasets that challenge conventional processing methods. In contrast, Sam and Chatwin (2018) characterize BDA as an innovative technology with the potential to generate business value through its unique capabilities in analytics, prediction, and decision support. Research conducted by Abdulkadri et al. (2016) and Bhadani and Jothimani (2016) underscores several critical dimensions and characteristics of BD, prominently including its substantial volume, diverse variety encompassing various data types and formats, and the rapid velocity at which data is generated, accumulated, and processed. BD Volume pertains to the considerable influx of data from diverse sources, BD Variety includes an extensive array of data types and formats, and BD Velocity often involves swift data generation, accumulation, and processing, sometimes in real-time or near-real-time. In this research, BD is delineated as a substantial dataset harboring numerous variables and high-velocity data. Mastery of BD analysis is indispensable for organizations seeking to leverage its advantages, make informed decisions, and gain competitive edges. These dimensions and attributes

underscore the unparalleled nature of BD and the challenges and prospects it brings to the forefront in terms of data management, analytics, and decision-making.

Understanding Big Data Analytics (BDA)

Understanding BDA involves delving into its foundational concepts, methodologies, challenges, and practical applications. This comprehensive exploration defines the boundaries of BDA's domain and reveals its transformative impact on information analysis, reshaping established paradigms in the process. BDA revolves around the extraction of patterns, trends, and insights from extensive datasets, guiding decision-making and enhancing business value. As highlighted by Lutfi et al. (2022), BDA's significance has steadily risen, gaining recognition from both scholars and practitioners for its potential benefits, challenges, and anticipated rewards. BDA requires advanced technologies, techniques, and algorithms to analyze diverse data types, including structured and unstructured data, often in real-time or near-real-time settings. Weibl and Hess (2018) intricately define BDA as a collection of methods and technologies used by enterprises to manage large volumes of complex data. This perspective is reinforced by Agrawal (2015) and Surbakti et al. (2020), who emphasize big data as an expansive dataset with immense potential for analysis, sharing, and the extraction of insightful revelations. Kalim (2021) identified several commonly used data mining techniques, including regression, nearest neighbor, clustering, and classification, each serving specific purposes in data analysis. Additionally, Kalim (2021) highlighted various tools and systems such as MongoDB, Hadoop, MapReduce, Orange, and Weka, which facilitate the management and mining of large datasets, leveraging algorithms for various data mining tasks. The exploration of BDA reveals its crucial role in deriving insights from extensive datasets through advanced technologies and methodologies. This foundational understanding addresses RQ1: What is the extent of BDA technology adoption within the HEIs? by showcasing the methodologies and technologies integral to BDA. Additionally, it provides a basis for evaluating RQ3: To what extent is the HEIs ready to adopt BDA technology? by highlighting the required technologies and skills.

Barriers to the Adoption of BDA

BDA technology provides organizations with invaluable data-driven insights, offering numerous benefits such as improving services, strengthening customer relationships, transforming business models, discovering new business opportunities, boosting operational efficiency, and gaining a competitive edge (Bhadani & Jothimani, 2016; Jeble et al., 2018; Surbakti et al., 2020; Ularu et al., 2012). According to Rogers (1995), several intrinsic characteristics of an innovation influence its diffusion: (1) Relative Advantage: How improved an innovation is over the previous generation, (2) Simplicity (or complexity): Whether an innovation is easy or difficult to use, and (3) Compatibility: Whether an innovation is compatible with current practices, values, and needs. In BDA technology, diffusion is hindered by various obstacles across its diverse components, including hardware, software, policies, skill sets, and data intricacies. To capitalize on the potential of big data, unconventional tools like parallel and cloud computing become indispensable in overcoming these barriers (Acharjya & Kauser, 2016). Extensive past research has delved deeply into the dimensions of these barriers. For instance, in a study conducted by Moktadir et al. (2019), researchers explored the primary impediments to BDA adoption in supply chain development within Bangladesh. Their findings underscored that the most substantial barriers encompassed insufficient infrastructure, challenges tied to data integration, concerns about data privacy, limited accessibility to BDA tools, and high investment costs. Their study revealed that in Bangladesh, the central hurdles obstructing BDA adoption are the absence of adequate infrastructure, the complexities tied to data integration, worries about data privacy, the constrained availability of BDA tools, and the financial burden of investment. Similarly, Park & Kim (2021) investigated the factors influencing the adoption of BD by Korean corporations and pinpointed influential aspects such as managerial support, security, privacy considerations, government backing, and policy frameworks. Correspondingly, Walker and Brown (2019) scrutinized a prominent South African telecommunications entity and identified top management support, human resource expertise, alignment of business and IT, and organizational size as pivotal organizational factors guiding the BDA adoption journey. In the pursuit of comprehending barriers to BDA adoption, Brohi et al. (2016)

highlighted a range of challenges including data storage and transfer complexities, scalability issues, data quality concerns, intricacies of data, timeliness, protection, privacy matters, trust considerations, data ownership questions, and transparency aspects. Similarly, a study undertaken in South Africa by Malaka and Brown (2015) exposed challenges like data privacy, return on investment, data quality, cost factors, data integrity, efficiency and scalability concerns, ownership and control matters, skill shortages, market priorities, training needs, and ambiguous processes as key hurdles to BDA adoption. In line with Agrawal (2015), a study conducted in China and India recognized data complexity, accessibility hurdles, regulatory approvals, organizational size, profitability considerations, and environmental uncertainties as the major obstacles hampering BDA adoption. Notably, numerous studies within developing nations, such as Lutfi et al. (2022), explored motivations for BDA adoption in Jordan, revealing influential factors like organizational readiness, top management support, security, complexities, and governmental backing. Moreover, Youssef et al. (2022) adopted a quantitative approach to scrutinize the factors influencing the adoption of BDA among retailers in the United Arab Emirates and Egypt. They concluded that concerns about security, external support, managerial backing, and a rational decision-making culture significantly impact BDA adoption in developed countries. The identification of barriers to BDA adoption provides insights into RQ2: What are the barriers hindering the implementation of BDA in HEIs? by detailing various obstacles identified in previous research. This also directly relates to RQ4: How do BDA barriers affect BDA technology adoption in HEIs? by explaining how these challenges impact the overall adoption process. Drawing from existing literature, this study categorizes the 44 sub-barriers to BD adoption into four distinct groups: technological hindrances, data-related challenges, legal considerations, financial obstacles, skill and knowledge shortages, and organizational factors, as outlined in Table 1.

Table 1. Barriers Influencing the Adoption of BDA in the Literature

No.	Sub-barriers	References
A. Technology Barriers		
1.	Absence of BDA tools, and data application capacities.	(Gómez & Heeks, 2016; Moktadir et al., 2019)
2.	Lack of infrastructural facility	(Moktadir et al., 2019; Rubinfeld & Gal, 2017; Sam & Chatwin, 2018; Surbakti et al., 2020; Wahab et al., 2021)
3.	Lack of interest in implementing new technology	(Moktadir et al., 2019)
4.	Network effects	(Moktadir et al., 2019; Rubinfeld & Gal, 2017; Sam & Chatwin, 2018)
5.	Storage and use of BD	(Brohi et al., 2016; Rubinfeld & Gal, 2017; Sivarajah et al., 2017)
6.	Technological and methodological challenges	(Khan, 2022; Rubinfeld & Gal, 2017; Schade, 2015)
B. Data Barriers		
1.	Complexity of data	(Brohi et al., 2016; Khan, 2022; Moktadir et al., 2019; Sam & Chatwin, 2018; Sivarajah et al., 2017; Surbakti et al., 2020; Youssef et al., 2022)
2.	Data Aggregation, Entry, and Integration	(Malaka & Brown, 2015; Moktadir et al., 2019; Schade, 2015; Sivarajah et al., 2017)
3.	Data quality issues	(Balachandran & Prasad, 2017; Brohi et al., 2016; Malaka & Brown, 2015; Moktadir et al., 2019)

No.	Sub-barriers	References
4.	Information Barriers	(Rubinfeld & Gal, 2017; Schade, 2015)
5.	data Variety	(Lutfi et al., 2023; Schade, 2015)
6.	data volume	(Gómez & Heeks, 2016; Schade, 2015)
7.	Velocity	(Lutfi et al., 2023; Schade, 2015)
8.	Data and Information Sharing	(Gómez & Heeks, 2016; Sivarajah et al., 2017)
9.	input/output data flow	(Sivarajah et al., 2017)
10.	data could be false or misleading	(Abdulkadri et al., 2016)
C. Legal Barriers		
1.	Data security and legal Concerns	(Balachandran & Prasad, 2017; Brohi et al., 2016; Gómez & Heeks, 2016; Lutfi et al., 2022; Moktadir et al., 2019; Rubinfeld & Gal, 2017; Sam & Chatwin, 2018; Youssef et al., 2022)
2.	Privacy	(Brohi et al., 2016; Gómez & Heeks, 2016; Malaka & Brown, 2015; Moktadir et al., 2019; Rubinfeld & Gal, 2017; Sivarajah et al., 2017; Surbakti et al., 2020)
3.	Data Protection	(Rubinfeld & Gal, 2017)
4.	Data Ownership and control	(Brohi et al., 2016; Malaka & Brown, 2015; Sivarajah et al., 2017)
5.	Foundation of laws and regulations	(Gómez & Heeks, 2016)
D. Financial Barriers		
1.	Lack of funding	(Moktadir et al., 2019; Sam & Chatwin, 2018; Sivarajah et al., 2017)
2.	High cost of investment and Return on Investment	(Malaka & Brown, 2015; Rubinfeld & Gal, 2017; Sivarajah et al., 2017)
3.	Access Prices and Conditions	(Rubinfeld & Gal, 2017)
4.	Lock-in and Switching Costs	(Rubinfeld & Gal, 2017)
E. Skills & Knowledge Barriers		
1.	Lack of skilled IT personnel	(Gómez & Heeks, 2016; Malaka & Brown, 2015; Moktadir et al., 2019; Sam & Chatwin, 2018; Sivarajah et al., 2017)
2.	Lack of facilities to research and develop BDA tools	(Moktadir et al., 2019; Sam & Chatwin, 2018; Sivarajah et al., 2017)
3.	Lack of training facilities	(Malaka & Brown, 2015; Moktadir et al., 2019)
4.	Sharing experiences between any two parties	(Schade, 2015)
5.	Aware of knowledge of BD	(Gómez & Heeks, 2016; Schade, 2015)
6.	Data Analysis and Modeling	(Sivarajah et al., 2017)
7.	Formats are completely understood by other systems	(Sivarajah et al., 2017)

No.	Sub-barriers	References
8.	Understanding the data architecture	(Abdulkadri et al., 2016)
F. Organizational Barriers		
1.	No policy to share data among organizations	(Gómez & Heeks, 2016; Moktadir et al., 2019)
2.	Semantic barrier	(Schade, 2015)
3.	Cultural and political issues	(Gómez & Heeks, 2016; Schade, 2015)
4.	Two-level entry	(Rubinfeld & Gal, 2017)
5.	Two-sided markets	(Rubinfeld & Gal, 2017)
6.	Foundational capabilities of relevance to BD	(Gómez & Heeks, 2016; Lutfi et al., 2023)
7.	Lack of top management commitment	(Lutfi et al., 2022; Youssef et al., 2022)
8.	Insufficient commitment or resistance to change of non-IT project stakeholders	(Weibl & Hess, 2018)
9.	Disabling data-collecting software	(Rubinfeld & Gal, 2017)
10.	Limited availability of BD for the public sector	(Balachandran & Prasad, 2017; Gómez & Heeks, 2016)

Table 1 lists various barriers to the adoption of BDA technology, as well as the sub-barriers that fall under each main barrier. The main barriers are grouped into six categories: technology, data, legal, financial, skills and knowledge, and organizational barriers. The technology category includes barriers such as the lack of availability of specific BDA tools, data science capabilities, and data application capabilities, as well as a lack of infrastructural facility and network effects. The data category includes barriers such as complexity of data, data aggregation, entry, and integration, data quality issues, and data volume. The legal category includes barriers such as data security and legal concerns, privacy, and data protection. The financial category includes barriers such as a lack of funding, high cost of investment and return on investment, access prices and conditions, and lock-in and switching costs. The skills and knowledge category includes barriers such as a lack of BDA expertise, lack of organizational readiness, and a lack of top management support. To gain a deeper understanding of how these barriers influence the adoption of BDA in the HEIs, we have developed the following hypotheses:

H1: Barriers associated with BD have a negative impact on BDA adoption in HEIs.

H2: Barriers associated with BD have a negative impact on the readdresses for BDA adoption in HEIs.

Research Methodology

The focus of this research is to explore the adoption of BDA technology within the Gaza Strip while investigating the impediments that hinder its effective utilization. To accomplish this goal, a quantitative research methodology was implemented, involving the design and distribution of an online questionnaire to 305 participants via email and social media. The questionnaire served as a pivotal instrument for gathering data and insights from respondents, providing valuable information on the status of BDA adoption and the challenges encountered within HEIs. It was organized into three main sections:

1. The first part of the survey assessed the extent of BDA technology utilization in the Gaza Strip (see Appendix A). This section aimed to measure the current adoption of BDA technologies within HEIs in the region. Understanding this is crucial as it establishes a baseline for BDA technology usage among educational institutions, enabling the assessment of readiness for deeper integration and

identification of areas needing improvement.

2. The second part of the survey evaluated the readiness of enterprises in the region to adopt BDA technology (see Appendix B). This section aimed to gauge the readiness of enterprises within the Gaza Strip to embrace BDA technology. It provided insights into organizational preparedness and receptiveness towards adopting innovative technologies like BDA.
3. The third part of the survey assessed six dimensions of barriers to BDA adoption, covering technology, data, legal, financial, skills and knowledge, and operational barriers (see Appendix C). This section aimed to identify and quantify the obstacles hindering the adoption of BDA technologies within HEIs in Gaza. Understanding these barriers is essential for devising tailored strategies to address challenges and promote more seamless adoption of BDA technologies.

This structured approach ensured comprehensive coverage of key aspects related to BDA adoption and barriers within HEIs, facilitating a thorough analysis of the research objectives. Respondents provided their input using a five-point Likert scale. Subsequently, statistical techniques like factor analysis and multiple regression were employed to analyze the collected data. Ensuring the questionnaire's reliability and construct validity was an integral part of the analysis process. The outcomes of this analysis were utilized to scrutinize the study's hypotheses and to formulate multiple regression equations. These equations are exemplified in equation (E1):

$$Y = a + b1X1 + b2X2 + b3X3 + \ldots + bnXn + e \quad (E1)$$

Explanation: Y: Dependent variable, Xi: Independent variable, b: Slope of the line, representing the influence of X on Y, a: Constant term, e: Error term

Sampling

This study focused on individuals working within both the public and private sectors in Gaza. The sampling approach involved a random selection of 305 respondents, as detailed in Table 2.

Table 2. Participant Demographics

Characteristics		**Sample Number**	**Percentage %**
Gender	Male	187	61.3
	Female	118	38.7
Education	Postgraduate	135	44.3
	Undergraduate	170	55.7
Experience/Years	Less than 5 years	95	31.1
	Between 5 and 10 years	76	24.9
	More than 10	134	43.9
Job Classification	Academic	141	46.2
	Administrative	164	53.8

Table 2 displays the characteristics of the sample employed in the study. A total of 305 respondents participated, with 61.3% being male and 38.7% being female. In terms of educational background, 44.3% of the respondents held postgraduate degrees, while the remaining 55.7% possessed undergraduate education. Concerning professional experience, 31.1% had less than 5 years of experience, 24.9% had between 5 and 10 years of experience, and 43.9% had more than 10 years of experience. The respondents were categorized based on their job classification: 46.2% were academics and 53.8% were administrative staff, 33.4%. These characteristics provide a comprehensive overview

of the sample utilized in the study. With professionals in HEIs in Gaza considered, 305 respondents provide a meaningful representation to garner insightful perspectives. This sample size ensures a comprehensive range of viewpoints across different sectors, experience levels, and educational backgrounds. Moreover, a sample size of 305 enables robust statistical analyses like factor analysis and multiple regression, ensuring the reliability and validity of the results. The sample encompasses a diverse mix of genders, education levels, job classifications, and years of experience, thereby enhancing the generalizability of findings to the broader HEIs population in Gaza.

Reliability Analysis

To gauge the reliability of the scale utilized in the study, the internal consistency was evaluated using Cronbach's alpha. This statistical measure assesses the reliability of a scale. For this study, the calculated Cronbach's alpha value was 0.88, signifying a strong level of consistency among the items within the instrument.

Reduction of Dimensionality in the BD Barriers Instrument

Principal Component Analysis (PCA) serves as a statistical technique to streamline the dimensions of a research instrument. Within this study, PCA was conducted to delineate the dimensions linked to the obstacles impeding BDA adoption in Gaza. This approach relies on both Eigenvalues and cross-loading patterns to ascertain the quantity of dimensions inherent in the instrument. Eigenvalues hold significant value; components possessing Eigenvalues surpassing one are more impactful, while those falling below one hold less relevance. Cross-loading denotes the distribution of items across two or more dimensions. The process involved applying component analysis and varimax rotation to 29 survey items from 305 participants, which are relevant to BD barriers dimensions. The findings revealed five dimensions with Eigenvalues exceeding 1.0. Additionally, four items were excluded from the analysis due to detected cross-loading: lack of specific BDA tools, lack of interest in applying new technology by the organization, lack of data storage facilities, and complexity of data. The remaining items and their estimated factor loadings with correlated factors are detailed in Table 3.

Table 3. Results of Factor Analysis

Factors	Items				
	1	2	3	4	5
Factor1: Infrastructure Barriers					
1. Bad Network infrastructure	.513				
2. Lack of software	.633				
3. Lack of Hardware	.599				
4. Data Aggregation	.557				
5. Data Integration	.825				
6. Data Performance and scalability	.840				
7. Lack of data entry team	.524				
8. No shared data within the organization	.595				
9. The data could be false or misleading	.746				
10. Lack of data format	.734				
Factor2: Security Barriers					

Factors	Items				
	1	2	3	4	5
1. Data Protection		.494			
2. Establishing information security mechanisms		.867			
3. Data privacy		.801			
4. laws and regulations related to BDA		.824			
Factor3: Financial Barriers					
1. funding for BDA			.679		
2. High cost of investment			.791		
3. Access Prices and Conditions list			.743		
4. The Cost/Operational Expenditures			.797		
Factor4: Skills & Knowledge Barriers					
1. aware of BDA				.673	
2. Lack of BDA skills				.581	
3. Research and develop BDA tools				.487	
4. Share the experiences				.689	
Factor5: Data Characteristics Barriers					
1. Data Variety					.734
2. Data volume					.847
3. Data Velocity					.690

Table 3 shows the results of the factor analysis conducted on the items measuring the barriers to BDA adoption. Five factors were identified, including infrastructure barriers, security barriers, financial barriers, skills and knowledge barriers, and data characteristics barriers. The items measuring infrastructure barriers included bad network infrastructure, lack of software, lack of hardware, data aggregation, data integration, data performance and scalability, lack of data entry team, lack of shared data within the organization, the possibility of false or misleading data, and lack of data format. The items measuring security barriers included data protection, establishment of information security mechanisms, data privacy, and laws and regulations related to BDA. The items measuring financial barriers included funding for BDA, high cost of investment, access prices and conditions, and cost/operational expenditures. The items measuring skills and knowledge barriers included awareness of BDA, lack of BDA skills, research and development of BDA tools, and sharing of experiences. Finally, the items measuring data characteristics barriers included data variety, data volume, and data velocity.

Results

This section presents the outcomes of the research study focused on the implementation challenges of BDA in HEIs. The results of various analyses, including the assessment of BDA practice, the impact of BDA barriers on readiness, and the relationship between readiness and practice, are discussed comprehensively. The section aims to provide a thorough understanding of the findings and their implications in navigating the hurdles of implementing BDA technology in the unique

context of HEIs.

Descriptive Analysis

In this section, we delve into the descriptive analysis of the research findings. This involves presenting and interpreting the collected data to gain insights into the current state of BDA adoption and the associated challenges, which address the research questions denoted as RQ1, RQ2, and RQ3. By analyzing the data from different perspectives, we aim to shed light on the extent of BDA technology practice and readiness, as well as the prominent barriers hindering its successful implementation. Through this analysis, we aim to provide a comprehensive overview of the situation on the ground, facilitating a deeper understanding of the dynamics surrounding BDA adoption in this specific context.

Practice of BDA Technology

Table 4 presents the results of a survey conducted to evaluate the extent of BDA technology implementation in HEIs. The survey included 11 questions derived from a literature review (Gómez & Heeks, 2016; Moktadir et al., 2019; Lutfi et al., 2022; Malaka & Brown, 2015; Sam & Chatwin, 2018; Sivarajah et al., 2017). Each question was answered using a five-point Likert scale. The table provides the mean value for each question, along with the percentage of respondents who agreed or strongly agreed with each statement. The results show that, overall, the organization has a high level of BDA technology practice, with most respondents agreeing or strongly agreeing that they can analyze BD, store the results of analyzing BD, share the results with others in the organization, and use BD to make decisions. The results also show that the organization provides technical assistance for BDA, and that the enterprise benefits from BD analysis to increase its competitiveness. Nevertheless, certain aspects of BDA technology practice in the Gaza Strip exhibit a lower level of development. Specifically, challenges are observed in terms of the ease and affordability of the BDA process, as well as the accessibility and usability of the technology for external parties or individuals. These areas require attention and improvement to enhance the overall effectiveness and inclusiveness of BDA practices in the region.

Table 4. BDA Technology Practice

No	Practice Factors	Mean	%	Rank
1.	You can analyze BD in this organization.	3.49	69.8	5
2.	You can store the result of analyzing the BD.	3.43	68.6	6
3.	You can store the reformulated result of BDA.	3.34	66.8	8
4.	This organization provides technical assistance for BDA.	3.66	73.2	2
5.	You can share the results of the BDA with others in the organization.	3.42	68.4	7
6.	BDA is easy and inexpensive.	2.68	53.6	9
7.	Anyone outside the organization can use BDA technology.	2.45	49	10
8.	The BDA process does not take a long time.	2.45	49	11
9.	The enterprise benefits from BD analysis to increase its competitiveness	3.83	76.6	1
10.	The organization uses BD to make decisions	3.58	71.6	4
11.	The organization uses BD in customer service, customer retention and acquisition.	3.60	72	3
The Gaza Strip BDA Practice Level is 65.33%				

Readiness for BDA Technology Adoption

Referring to Table 5, the findings demonstrate a keen interest among firms in embracing new technologies; however, their ability to do so is constrained by limited financial resources and restricted access to BDA expertise and training. Additionally, the absence of regulatory frameworks pertaining to BDA in the Gaza Strip, coupled with partial support from top management and an unwillingness to acknowledge potential risks, further hinders BDA adoption. Despite possessing a robust foundation in terms of data and IT infrastructure, various obstacles remain that must be tackled to fully harness the advantages of BDA technology.

Table 5. BDA Technology Readiness

No.	Practice Factors	Mean	%
1.	The Employees of this organization are aware of the importance of BDA	3.43	68.6
2.	This organization is interested in applying new technology	3.34	66.8
3.	The organization has a strong information network	3.70	74
4.	The organization has sufficient data storage facilities	3.46	69.2
5.	The organization has good data.	3.75	75
6.	There is a team in the organization to enter data.	3.89	77.8
7.	There is a mechanism within the organization to monitor the data.	3.59	71.8
8.	The organization's employees have exclusive rights to use, compile, select, structure, and re-format organizational Data.	3.49	69.8
9.	This organization has laws and regulations related to BDA	3.04	60.8
10.	The organization allocates sufficient funding for BDA	2.99	59.8
11.	The company has prepared data Access Prices and Conditions list	2.78	55.6
12.	Employees are trained in BDA skills	2.78	55.6
13.	There are facilities to research and develop BDA tools	2.91	58.2
14.	The data architecture in this organization is completely understood	3.51	70.2
15.	A culture exists in this organization that promotes BDA Practices	3.39	67.8
16.	Top management supports the adoption of BDA	3.35	67
17.	Top management accepts possible risks which may result from adopting BDA	3.28	65.6
The Gaza Strip BDA Readiness Level is 66.68%			

The results from the assessment of BDA readiness, as presented in Table 5, demonstrate that the HEIs has a robust information network, sufficient data storage infrastructure, and commendable data quality. Nevertheless, room for enhancement exists, including the allocation of sufficient funds for BDA initiatives, formulation of pricing and access conditions for data, and provision of training to cultivate BDA competencies. In aggregate, the HEIs attains a readiness level of 66.68% for the implementation of BDA technology. Addressing these identified shortcomings is crucial for the HEIs to maximize the potential benefits derived from the integration of BDA technology.

Barriers to the Adoption of BDA Technology

To respond to RQ2, participants were surveyed regarding the 29 obstacles in adopting BDA, which are discussed later in Table 6. Subsequently, the average responses were calculated and arranged in order of significance, as detailed in Table 6. According to the data presented in Table 6, the most significant barriers identified are "Funding for BDA" with a mean score of 4.03 and a high agreement percentage of 80.6%, followed closely by "Access Prices and Conditions list" with a mean score of 3.89 and an agreement percentage of 77.8%. Other noteworthy barriers include "High cost of investment" (mean score: 3.85, agreement: 77.0%), "Lack of BDA skills" (mean score: 3.85, agreement: 77.0%), and "Share the experiences" (mean score: 3.83, agreement: 76.6%). Barriers related to data complexities, such as "Data volume," "Data Variety," and "Data Velocity," also hold notable positions in the rankings, showcasing the challenges associated with managing and processing diverse data types. Additionally, challenges pertaining to technology infrastructure, organizational interest in new technology, data integration, and data privacy are identified as significant barriers. The provided data reveals the intricacies and varied factors that hinder BDA adoption within the Gaza Strip, shedding light on areas that require focused attention and intervention for the successful implementation of BDA technology.

Table 6. BDA Barriers

No.	Barriers Factors	Mean	%	Rank
1.	Lack of specific BDA tools	3.72	74.4	9
2.	Bad Network Infrastructure	3.28	65.6	16
3.	The organization is not interested in applying new technology	3.51	70.2	11
4.	Lack of software this organization	2.97	59.4	25
5.	Lack of Hardware this organization	3.34	66.8	14
6.	Lack of data storage facilities	3.22	64.4	19
7.	The complex data	2.72	54.4	29
8.	Data Aggregation	2.75	55	28
9.	Data Integration	3.12	62.4	20
10.	Data Performance and scalability	2.98	59.6	24
11.	Data Variety	3.58	71.6	10
12.	Data volume	3.49	69.8	12
13.	Data Velocity	3.28	65.6	17
14.	Lack of data entry team	3.00	60	22
15.	No shared data within the organization	3.25	65	18
16.	Data Protection	2.85	57	27
17.	The data could be false or misleading	3.00	60	23
18.	Lack of data format	3.05	61	21
19.	Establishing information security mechanisms	3.31	66.2	15
20.	Data privacy	2.91	58.2	26
21.	Laws and regulations related to BDA	3.48	69.6	13

No.	Barriers Factors	Mean	%	Rank
22.	Funding for BDA	4.03	80.6	1
23.	High cost of investment	3.85	77	3
24.	Access Prices and Conditions list	3.89	77.8	2
25.	The Cost/Operational Expenditures	3.83	76.6	5
26.	Aware of BDA	3.82	76.4	7
27.	Lack of BDA skills	3.85	77	4
28.	Research and develop BDA tools	3.80	76	8
29.	Share the experiences	3.83	76.6	6

The findings of this study are consistent with those of several other studies, underscoring financial constraints as a significant barrier. These challenges include insufficient funding, high investment costs, and strict access conditions (e.g., Rubinfeld & Gal, 2017; Moktadir et al., 2019). Additionally, like other research, this study also identifies shortages in skilled personnel and inadequate training facilities as recurring themes (e.g., Gómez & Heeks, 2016; Malaka & Brown, 2015).

Regression Analysis

To investigate the research hypotheses (H1 and H2), stepwise regression was employed to evaluate how barriers to BDA influence both BDA readiness and practice. Section 6.2.1 delved into the evaluation of BDA barriers on BDA preparedness, while Section 6.2.2 provided a comprehensive examination of the influence of BDA barriers on BDA readiness.

Influence of BDA Barriers on BDA Practice

To assess the first research hypothesis (H1), this study utilized a stepwise regression approach to explore how barriers to BDA impact the actual practice of BDA. The outcomes of this analysis are presented in Table 7.

Table 7. Influence of BDA Barriers on BDA Practice

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	4.175	.386		10.803	.000
1	Security Barriers	-.137-	.058	-.195-	-2.359-	.020
2	Financial Barriers	-.317-	.068	-.363-	-4.631-	.000
3	Skills Barriers	-.268-	.062	-.343-	-4.339-	.000
4	Data Characteristics	-.175-	.062	-.193-	-2.840-	.005

Where R=0.429, R^2=0.184, Adjusted R^2=.130, F value=3.381, Sig. F=0.008

The regression analysis indicates that the value of R is 0.429 and the p-value is 0.008, which indicates that BD barriers and BDA practice are positively related. The R Square = 0.184 states that 18.4% of the total variance in the dependent variable (BDA practice) is explained by BD barriers. Based on these results, the multi regression predicated as the equation (E2):

BDA Practice = 4.175 - .137 Security Barriers - .268 Skill Barriers - .317 Financial Barriers -.175 Data Characteristics + e (E2)

The equation denoted as E2 suggests that addressing challenges related to security, financial considerations, data characteristics, and BDA skill barriers would have a negative impact on the adoption of BDA practices.

Influence of BDA Barriers on BDA Readiness

The outcomes of the regression analysis between barriers to BDA and the readiness for BDA are presented in Table 8.

Table 8. Influence of BDA Barriers on BDA Readiness

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	4.560	.442		10.326	.000
1	Security Barriers	-.165-	.058	-.233-	-2.846-	.005
2	Infrastructure Barriers	-.165-	.070	-.194-	-2.348-	.020
3	Financial Barriers	-.300-	.070	-.341-	-4.313-	.000
4	Skills Barriers	-.348-	.059	-.442-	-5.846-	.000

Where R=0.422, R 2=0.178, Adjusted R2=.123, F value=3.241, Sig. F=0.01

The analysis presented in Table 8 demonstrates that IT infrastructure barriers, security, financial, and skills barriers have an adverse impact on BDA readiness. This implies that as the levels of these barriers increase, the readiness to adopt BDA technology decreases. The regression analysis further reveals the significance of the relationship between BDA barriers and BDA readiness, with a value of R = 0.422 and a p-value of 0.01. Moreover, the R Square value of 0.178 indicates that BDA barriers can explain 17.8% of the variability in BDA readiness. Consequently, the multi-regression equation for predicting BDA readiness is as follows:

BDA readiness = 4.560 - .165 Infrastructure Barriers – .165 Security- .348 Skill Barriers - .300 Financial Barriers + e (E3)

The equation labeled as E2 indicates that enhancing IT infrastructure, skills relevant to BDA, security measures, and addressing financial concerns will yield a negatively impact on the preparedness for BDA adoption in the Gaza Strip. However, it is important to note that the model only explains 17.8% of the variance in BDA readiness. Based on the outcomes of the preceding analysis, the associations between the independent variables (BDA Barriers) and the dependent variables (BDA Practice and BDA Readiness) are illustrated in Figure 1.

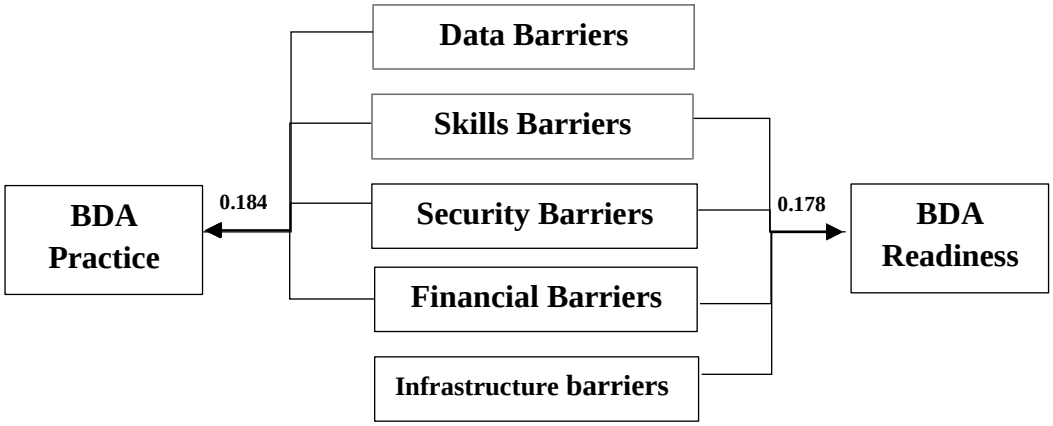

Figure 1. Barriers to BDA Adoption Model

Discussion

This study highlights several critical insights into the adoption and utilization of BDA technology within HEIs in the Gaza Strip. The assessment of BDA practices revealed a predominantly positive outlook among these institutions. They demonstrated a commendable ability to analyze Big Data, store and share results within their organizational frameworks, and utilize insights for decision-making processes. These capabilities highlight a foundational readiness to harness the potential benefits of BDA in enhancing operational efficiencies and strategic decision-making. However, the study also identified areas for improvement, particularly in enhancing the affordability and accessibility of BDA technologies. Financial barriers pose a significant challenge to HEIs in Gaza, primarily due to the socio-economic and political context of the region. These barriers include insufficient funding and high investment costs. HEIs in Gaza frequently encounter severe financial shortages due to constrained budgets and limited external funding opportunities. This constraint significantly impedes their capacity to invest in costly technologies such as BDA, which necessitate substantial initial investments in infrastructure, software, and training. Addressing these financial barriers is crucial for HEIs in Gaza to enhance their technological capabilities and overcome obstacles to BDA adoption. It requires targeted interventions, international support, and strategic investments aimed at fostering sustainable development and resilience in higher education amidst challenging socio-economic conditions. In contrast, obstacles related to IT infrastructure appear to have minimal influence on BDA, as suggested by the viewpoints of the survey participants. Based on these findings, it is recommended that organizations in the Gaza Strip focus their efforts on strengthening security measures, promoting skill development, and strategically investing in BDA. This approach can enhance the overall quality of their BDA initiatives.

Implications

The findings of this study have several implications for policy makers, educational leaders, and practitioners seeking to promote BDA adoption in Gaza's educational sector. Addressing financial barriers through targeted funding mechanisms and resource allocation strategies is imperative to facilitate sustainable investments in BDA infrastructure and capabilities. Enhancing regulatory frameworks to clarify data access conditions and promoting organizational readiness through leadership support and capacity building initiatives are crucial steps towards fostering a conducive environment for BDA adoption. Furthermore, fostering collaborations between academia, industry, and government entities can facilitate knowledge exchange and best practice sharing, mitigating barriers related to skills shortages and technological integration challenges. By prioritizing these strategic initiatives, stakeholders can leverage BDA technologies to drive innovation, enhance educational outcomes, and position Gaza's HEIs at the forefront of data-driven decision-making in the region.

Conclusion

This study has conducted a thorough investigation into the current state of BDA practices and the related barriers within the HEIs of the Gaza Strip. Additionally, it has assessed how these factors affect the readiness of institutions to adopt BDA technology. The study outcomes provide valuable insights into this domain. Initially, the investigation delineated five distinct dimensions of BDA barriers: infrastructure, security, financial, skills and knowledge, and data characteristics. Among these dimensions, the most pronounced obstacles within the Gaza Strip encompassed financial constraints, substantial investment costs, a dearth of BDA expertise, and limited knowledge sharing. Moreover, the study gauged the BDA practice level within the Gaza Strip at 65.3%, indicating a considerable level of adoption. Concurrently, the readiness to embrace BDA technology stood at 66.68%, highlighting potential for growth and further implementation. The regression analysis conducted revealed that security, financial factors, and skill barriers negatively influenced BDA adoption, explaining about 18.4% of the variances. On the other hand, barriers such as IT infrastructure, security, financial constraints, and skill limitations negatively affected BDA readiness, explaining around 17.8% of the variances. In contrast, barriers associated with data characteristics had relatively fewer notable effects. Derived from these findings, it is highly recommended that universities, collectives, and governmental bodies within the Gaza Strip proactively collaborate to dismantle existing BDA barriers. This can be facilitated through the development of a comprehensive governmental strategy that fosters widespread BDA technology adoption. Additional emphasis on enhancing IT infrastructure, augmenting BDA skill sets, and promoting awareness is essential. Future research endeavors should delve deeper into the specific challenges and opportunities encountered by local businesses in the context of BDA adoption. This will enable tailored interventions and targeted support mechanisms. Furthermore, exploring the potential advantages linked to BDA integration, including enhanced efficiency, competitive advantages, and improved decision-making capacities, can underscore the tangible value proposition of BDA technology for local enterprises, thereby motivating its broader adoption. In conclusion, addressing the identified barriers and fostering BDA adoption in the Gaza Strip can usher in advanced data analysis capabilities, furnishing businesses with a distinct competitive edge and contributing substantively to the region's overall growth and development. However, it is important to acknowledge the limitations of this study. Firstly, it concentrated solely on five specific factors affecting BDA adoption, potentially overlooking other significant factors that may also play a crucial role. Secondly, the scope of the research was confined to HEIs within the Gaza Strip, which may limit the generalizability of the findings to other regions or types of institutions. Therefore, caution should be exercised when applying these results to different contexts or broader populations.

References

Abdulkadri, A., Evans, A., & Ash, T. (2016). An assessment of big data for official statistics in the Caribbean: challenges and opportunities. Retrieved from https://hdl.handle.net/11362/39853

Acharjya, D. P., & Kauser, A. P. (2016). A survey on big data analytics: challenges, open research issues and tools. *International Journal of Advanced Computer Science and Applications*, 7(2), 511-518.

Agrawal, K. (2015). Investigating the determinants of Big Data Analytics (BDA) adoption in Asian emerging economies. *AMCIS 2015 Proceedings*. 25.

Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, 60(3), 285-292.

Aseeri, M., & Kang, K. (2023). Organisational culture and big data socio-technical systems on strategic decision making: Case of Saudi Arabian higher education. *Education and Information Technologies*, 1-26

Balachandran, B. M., & Prasad, S. (2017). Challenges and benefits of deploying big data analytics in the cloud for business intelligence. *Procedia Computer Science*, 112, 1112-1122.

Barakat, M. (2016). Challenges facing statistical agencies under the big data revolution: Case Study, Palestine. Retrieved from https://www.pcbs.gov.ps/papersar.aspx?lang=ar

Bedeley, R. (2014). Big Data opportunities and challenges: the case of banking industry. *SAIS 2014 Proceedings*. 2. https://aisel.aisnet.org/sais2014/2

Bhadani, A., Jothimani, D. (2016), Big data: Challenges, opportunities and realities, In Singh, M.K., & Kumar, D.G. (Eds.), Effective Big Data Management and Opportunities for Implementation (pp. 1-24), Pennsylvania, USA, IGI Global

Brohi, S. N., Bamiah, M. A., & Brohi, M. N. (2016). Identifying and analyzing the transient and permanent barriers for big data. *Journal of Engineering Science and Technology*, 11(12), 1793-1807.

Gomez, L., & Heeks, R. (2016). *Measuring the Barriers to Big Data for Development: Design-Reality Gap Analysis in Colombia's Public Sector*. (pp. 1-11). (GDI Development Informatics Working Papers; No. 62).

Jeble, S., Kumari, S., & Patil, Y. (2018). Role of big data in decision making. *Operations and Supply Chain Management: An International Journal*, 11(1), 36-44.

Kalim, U. (2021). The growing role of big data in education and its implications for educational leadership. *International Journal of Research and Innovation in Social Science*, 5(1), 257-262.

Khan, S. (2022). Barriers of big data analytics for smart cities development: a context of emerging economies. *International Journal of Management Science and Engineering Management*, 17(2), 123-131.

Li, J., Tao, F., Cheng, Y., & Zhao, L. (2015). Big data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology*, 81(1), 667-684.

Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Al-Khasawneh, A. L., Ibrahim, N. (2023). Drivers and impact of big data analytic adoption in the retail industry: A quantitative investigation applying structural equation modeling. *Journal of Retailing and Consumer Services*, 70, 103129.

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., Ibrahim, N, Saad, M. (2022). Factors Influencing the Adoption of Big Data Analytics in the Digital Transformation Era: Case Study of Jordanian SMEs. *Sustainability*, 14(3), 1802.

Malaka, I., & Brown, I. (2015). Challenges to the organisational adoption of big data analytics: A case study in the South African telecommunications industry. ACM International Conference Proceeding Series, Stellenbosch, South Africa, September 28–30, 2015.

Moktadir, M. A., Ali, S. M., Paul, S. K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers & Industrial Engineering*, 128, 1063-1075.

M. A. Nazarenko and T. V. Khronusova, "Big data in modern higher education. Benefits and criticism," *2017 International Conference "Quality Management,Transport and Information Security, Information Technologies" (IT&QM&IS)*, St. Petersburg, Russia, 2017, pp. 676-679

Park, J.-H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems*, 61(3), 285-293.

PCBS. (2021). Palestinian Central Bureau of Statistics, https://www.pcbs.gov.ps/Default.aspx

Rogers, E. M. (1995). Diffusion of innovation (4th ed.). New York, NY: The Free Press

Rubinfeld, D. L., & Gal, M. S. (2017). Access barriers to big data. Arizona Law Review, 59, 339.

Sam, K. M. & Chatwin, C. R. (2018). Understanding Adoption of Big Data Analytics in China: From Organizational Users Perspective, *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Bangkok, Thailand, 2018, pp. 507-510

Schade, S. (2015). Big Data Breaking Barriers--First Steps On A Long Trail. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 7(3), 691-697.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263-286.

Statista. (2022). Electronic waste worldwide https://www.statista.com/statistics/1067081/generation-electronic-waste-globally-forecast/

Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2020). Factors influencing effective use of big data: A research framework. *Information & Management*, 57(1), 103146.

Ularu, E. G., Puican, F. C., Apostu, A., & Velicanu, M. (2012). Perspectives on big data and big data analytics. *Database Systems Journal*, 3(4), 3-14.

Wahab, S. N., Hamzah, M. I., Sayuti, N. M., Lee, W. C., & Tan, S. Y. (2021). Big data analytics adoption: an empirical study in the Malaysian warehousing sector. *International Journal of Logistics Systems and Management*, 40(1), 121-144.

Walker, R. S., & Brown, I. (2019). Big data analytics adoption: A case study in a large South African telecommunications organisation. South *African Journal of Information Management*, 21(1), 1-10.

Weibl, J., & Hess, T. (2018). Success or failure of big data: Insights of managerial challenges from a technology assimilation perspective. Proceedings of the Multikonferenz Wirtschaftsinformatik (MKWI), 12-59.

Williams, P. (2017). Assessing collaborative learning: big data, analytics and university futures. *Assessment & Evaluation in Higher Education*, 42(6), 978-989.

Yousef, Y. A. (2023). Investigating the Role of Critical Success Factors in Achieving the Success of Agile Projects in the Gaza Strip. *CIT. Journal of Computing and Information* Technology, 30(2), 117-137.

Youssef, M. A. E.-A., Eid, R., & Agag, G. (2022). Cross-national differences in big data analytics adoption in the retail industry. *Journal of Retailing and Consumer Services*, 64, 102827.

Appendix A. BDA Readiness Measurement Questionnaire

Please use the checkmark (√) to indicate your level of approval on the following axes

GIT Awareness		Strongly agree	Agree	Moderate	Disagree	Strongly disagree
R1	You can analyze BD in this organization.					
R2	You can store the result of analyzing the BD.					
R3	You can store the reformulated result of BDA.					
R4	This organization provides technical assistance for BDA.					
R5	You can share the results of the BDA with others in the organization.					
R6	BDA is easy and inexpensive.					
R7	Anyone outside the organization can use BDA technology.					
R8	The BDA process does not take a long time.					
R9	The enterprise benefits from BD analysis to increase its competitiveness					
R10	The organization uses BD to make decisions					
R11	The organization uses BD in customer service, customer retention and acquisition.					

Appendix B. BDA Practice Measurement Questionnaire

Please use the checkmark (√) to indicate your level of approval on the following axes:

GIT Adoption		Strongly agree	Agree	Moderate	Disagree	Strongly disagree
P1	The Employees of this organization are aware of the importance of BDA					
P2	This organization is interested in applying new technology					
P3	The organization has a strong information network					
P4	The organization has sufficient data storage facilities					
P5	The organization has good data.					
P6	There is a team in the organization to enter data.					
P7	There is a mechanism within the organization to monitor the data.					
P8	The organization's employees have exclusive rights to use, compile, select, structure, and re-format organizational Data.					
P9	This organization has laws and regulations related to BDA					
P10	The organization allocates sufficient funding for BDA					
P11	The company has prepared data Access Prices and Conditions list					
P12	Employees are trained in BDA skills					
P13	There are facilities to research and develop BDA tools					
P14	The data architecture in this organization is completely understood					
P15	A culture exists in this organization that promotes BDA Practices					
P16	Top management supports the adoption of BDA					
P17	Top management accepts possible risks which may result from adopting BDA					

Appendix C. BDA Barriers Measurement Questionnaire

Please use the checkmark (√) to indicate your level of approval on the following axes:

GIT Adoption		Strongly agree	Agree	Moderate	Disagree	Strongly disagree
B1	Lack of specific BDA tools					
B2	Bad Network Infrastructure					
B3	The organization is not interested in applying new technology					
B4	Lack of software this organization					
B5	Lack of Hardware this organization					
B6	Lack of data storage facilities					
B7	The complex data					
B8	Data Aggregation					
B9	Data Integration					
B10	Data Performance and scalability					
B11	Data Variety					
B12	Data volume					
B13	Data Velocity					
B14	Lack of data entry team					
B15	No shared data within the organization					
B16	Data Protection					
B17	The data could be false or misleading					
B18	Lack of data format					
B19	Establishing information security mechanisms					
B20	Data privacy					
B21	Laws and regulations related to BDA					
B22	Funding for BDA					
B23	High cost of investment					
B24	Access Prices and Conditions list					
B25	The Cost/Operational Expenditures					
B26	Aware of BDA					
B27	Lack of BDA skills					
B28	Research and develop BDA tools					
B29	Share the experiences					

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Enhancing ERP Usage Through Absorptive Capacity: A Case Study from Indonesia Enterprise

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Abstract

Abstract—This research investigates the effect of individual users' absorptive capacity on Enterprise Resource Planning (ERP) usage at PT ABC, a transportation company in Indonesia. The current study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the connections between three aspects of absorptive ability and ERP usage. This study revealed that among aspects of absorptive capacity, only the capacity associated with applying ERP knowledge directly affects ERP usage. Meanwhile, prior understanding and proficiency in integrating ERP systems have a significant indirect impact on ERP usage performance. Based on these theoretical findings, it is suggested that PT ABC strengthens individual employees' absorptive capacities and encourages them to acquire ERP expertise before implementation. Moreover, cultivating a culture that supports collaboration and knowledge sharing is crucial for maximizing the benefits of ERP systems within the organization. Implementing these strategies is expected to improve ERP adoption outcomes at PT ABC.

Keywords: ERP, Absorptive Capacity, ERP Usage, PLS-SEM

Introduction

PT ABC, a reputable organization operating in Indonesia's transportation management industry, has been leading the way in embracing state-of-the-art solutions to improve the quality of its services, which include cargo handling, vehicle management, traffic intelligence, and real-time vehicle movement. The organization has implemented enterprise resource planning (ERP) systems across key departments, particularly Finance, Human Resources, Commerce, and Operations. This strategic move has significantly bolstered its daily business operations, demonstrating PT ABC's commitment to technological advancement and operational efficiency.

In its journey to fully harness the capabilities of the ERP systems, PT ABC has navigated various challenges following the implementation period. An internal audit conducted in the last financial year

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highlighted some areas of improvement, such as change management oversight, consistent documentation, and the need for dedicated roles to modify the system. Recognizing the importance of employee engagement in leveraging technology, the company has conducted multiple workshops and training sessions, complemented by establishing a comprehensive company-wide policy to integrate ERP into day-to-day operations.

Numerous businesses and organizations encounter the same hurdles PT ABC encountered during the ERP post-implementation period. According to a recent poll, the most challenging aspect of ERP for 33.3% of organizations is organizational change, which involves individuals within the company (Chang, 2024). This influences the management perspective since 4 of 5 IT Directors reported dissatisfaction with their ERP Project (Chang, 2024) This research utilizes the concept of absorptive capacity to advance in this specific field. Absorptive capacity refers to the individual ability to understand, assimilate, and exploit external knowledge (Haryanti & Subriadi, 2021).

Research has demonstrated that absorptive capacity positively impacts project success (Mata et al., 2023; Ramadhan et al., 2024). Mata et al. find that absorptive capacity, directly and indirectly, affects project success (Mata et al., 2023). The research conducted by Ramadhan et al. in 2024 underscores the critical role of absorptive capacity in enhancing project success, especially in environments marked by high complexity (Ramadhan et al., 2024). A study also demonstrates that preventing ERP project failure can be achieved by looking at the individual absorptive capacity that facilitates the organizational knowledge process and results in positive organizational capability development (Sharma et al., 2012). Absorptive capacity has also been proven to significantly relate to ERP implementation and assimilation (Saraf et al., 2013). Research on organizations that have adopted ERP systems reveal that assimilation, application, and transfer of information (which are important aspects of individual absorptive capacity) have beneficial impact on ERP usage performance (Park et al., 2007; Wang et al., 2007). The ERP usage model is based on the DeLone and McLean Model, because this model establishes a cause-and-effect relationship between individual and organizational impact (Zhang et al., 2005). It demonstrates how information affects the behavior of individuals and ultimately impacts organizational performance, aligning with the goal of PT ABC.

Identifying three parts of individual absorptive capacity in PT ABC is critical because the management team is now focused on identifying individual elements that affect the usage of ERP in business activities. Most importantly, ERP systems do not transfer the work and skills of information sources to knowledge consumers, making direct interactions with knowledge users almost impossible (Nandi & Vakkayil, 2018). This strategy is anticipated to greatly enhance the development of a more effective ERP adoption strategy, thereby improving productivity and efficiency

With the above information, this paper examines the correlation between individual user absorptive capacity and ERP usage performance at PT ABC. Moreover, no research has examined how individual absorptive capacity affects ERP adoption within Indonesia's transportation sector. This study looks at three parts of an individual's absorptive capacity: their existing knowledge of ERP systems, their proficiency in integrating new ERP information into their work, and their application of ERP information during their job performance (Park et al., 2007). This research will assist PT ABC in developing a more comprehensive approach to improve the adoption of ERP.

This study also has potential for a greater impact due to projected robust growth of ERP business in Indonesia over the upcoming years. The ERP market is projected to grow at a compound annual growth rate (CAGR) of 7.88%, generating revenue of US$118.10 million by 2028 (Statista, 2024). The forecasted data also indicates a 25% increase in per capita ERP software expenditure by 2028 compared to 2024 (Statista, 2024). This underscores the growing significance and adoption of ERP solutions in Indonesia

Literature Review

The ERP system unifies various fundamental processes in an organization by linking data and process flow, providing functionality, features, and capabilities (Nandi & Vakkayil, 2018). The adoption and implementation of ERP enhance company performance by centralizing data and information flow

across diverse functional areas and facilitating open innovation within an organization (Uddin et al., 2020).

It should be recognized that the performance of an ERP system is not primarily defined by early success. Organizations can anticipate long-term improvement in the post-implementation phase by consistently focusing on process enhancement, system integration, and system development (Hasan et al., 2019; Zhu et al., 2010). The performance of an ERP systems initiative is ultimately determined by post-implementation success, which primarily results from the advantage that organizations can gain from ERP deployment (Zhu et al., 2010). These determinants comprise support from top management, a proficient team, end-user education, and ongoing system development. These studies also yield several practical suggestions, including considering conflict of interest, modifying the system, and establishing change management initiatives (Hasan et al., 2019; Hsu et al., 2015; Zhu et al., 2010).

Absorptive Capacity

Absorptive capacity is generally characterized by human competencies, such as individual capability, motivation, knowledge exchange, and assistive capacity (Nandi & Vakkayil, 2018). Cohen defines absorptive capacity as an organization's capacity to recognize, incorporate, and effectively utilize knowledge from its external environment. (Cohen & Levinthal, 1990). The research also suggests that the firm's absorptive capacity is influenced by its members (Haryanti & Subriadi, 2021). Since introducing this new conceptual framework, the notion of absorptive capacity has undergone modifications, including how absorptive capacity plays a crucial role in helping firms develop and maintain competitive advantages through innovative uses of information technology. Boynton et al. state that absorptive capacity in the organization serves as a conceptual framework for the organization's IS understanding (Boynton et al., 1994).

Within the domain of ERP systems, individual absorptive capacity is categorized into three interconnected components (Park et al., 2007). The first aspect is understanding ERP systems. The degree to which the participants had prior knowledge about the objects (Cohen & Levinthal, 1990). This component involves understanding the user regarding ERP systems and consultancy companies (Park et al., 2007). The second element is the user's capacity to integrate newly learned knowledge from ERP technology into their work environment. This second component is called assimilating ERP systems. Upon grasping new knowledge, organizational members must assimilate it, which may be influenced by their comfort level with the associated technology. The final element, applying ERP systems, is the application of ERP knowledge to use on the job. Similar to problem-solving abilities, this is related to the ability of the users to enhance their work based on knowledge derived from ERP and teach that knowledge of ERP to others (Park et al., 2007).

Performance of ERP Usage

ERP system usage pertains to how users utilize the system's capabilities to complete tasks (Hallikainen & Seethamraju, 2015). System utilization is a crucial indicator of the effectiveness of information systems deployment. Therefore, for intricate systems like ERP, usage behavior must be in-depth and advanced for organizations to recognize the inherent advantages (Hallikainen & Seethamraju, 2015). In general, the more end users utilize the system, the higher the chances of the organization achieving its goals and objectives for implementing ERP.

The performance of ERP usage implies how individuals effectively utilize ERP systems to increase productivity and accomplish organizational goals (Chang et al., 2011). This can be quantified through metrics such as user satisfaction, effectiveness, and efficiency (Chang et al., 2011). Previous research has demonstrated that the advantages of ERP implementation are not exclusively contingent upon the technology itself but also depend on the organization's ability to integrate and capitalize on knowledge throughout the organization (Park et al., 2007; Sharma et al., 2012; Wang et al., 2007)

PLS-SEM

Partial least squares structural equation modeling (PLS-SEM) is employed as a statistical technique to quantify the relationships among multiple variables within a structural equation framework (Hair et al., 2017b). The PLS-SEM approach allows researchers to estimate intricate models that encompass many constructs, indicator variables, and structural paths, without requiring any assumptions about the distribution of the data (Hair et al., 2019). Constructs or latent variables are abstract notions that are unable to be observed immediately or measured (Hair et al., 2017b; Hair et al., 2019). These constructs embody conceptual aspects that researchers want to investigate. Indicator variables, often referred to as observed variables or items, are the specific data points gathered by surveys, observations, or other data collection techniques (Hair et al., 2017b; Hair et al., 2019). These variables are utilized to quantify the underlying constructions within the PLS-SEM framework. PLS-SEM is widely used by numerous studies employing this to identify causal links between several constructs with *various* indicators (Hair et al., 2017a; Hair et al., 2017b; Hair et al., 2019). Modelling in PLS-SEM can be classified as either reflective or formative, depending on the direction of causality between the construct and its indicators (Hair et al., 2017a; Hair et al., 2017b). Reflective constructions hold that the construct impacts its indicators, indicating that the indicators are expressions of the construct and should show a correlation (Hair et al., 2019). Formative constructions are created by their indicators, where each indicator contributes to the construct (Hair et al., 2019).

PLS-SEM is also suitable for doing research with a limited population and restricted sample size (Hair et al., 2019; Hair et al., 2017a). Many publications also use the PLS-SEM Model structural modeling approach for small-size samples (N < 100) (Hair et al., 2017b). Moreover, the availability of user-friendly software programs, such as PLS-Graph and SmartPLS, considerably improves the accessibility of PLS-SEM for researchers from various fields of study (Hair et al., 2019; Mayeh et al., 2016).

Research Methodology

Research Model

Figure 1 illustrates the framework utilized in this investigation., which examines the correlation between individuals perceived absorptive capacity and ERP usage in Korean firms (Park et al., 2007). The model observes how the three individual absorptive capacity components interact and correlate with ERP usage performance.

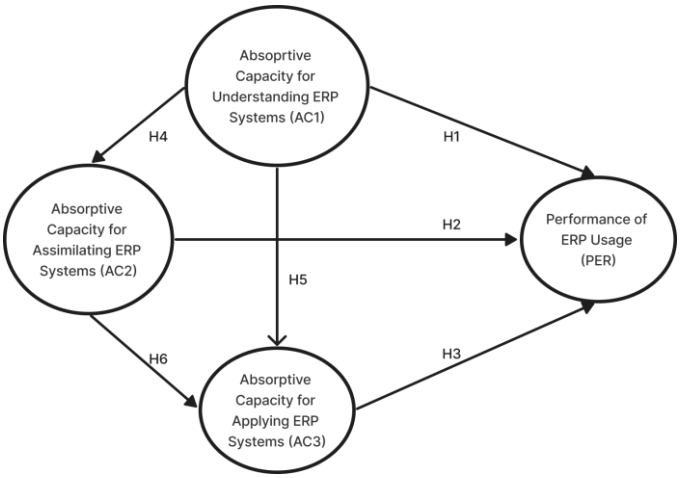

Figure 1. Research Model

Figure 1 presents the research model, which includes three constructs related to absorptive capacity and one construct concerning ERP usage performance. Each of these constructs will be quantified using second-level variables known as indicators. Table 1 summarizes these constructs, along with their corresponding indicators and definitions. Subsequent sections of the document will delve into the details

of three facets of individual absorptive capacity along with its impact on ERP usage performance, as investigated in this study.

Table 1. Summary of Absorptive Capacity Constructs and Indicators

Constructs	Indicators	Definition
AC1	CONK1, CONK2, CONK3, CONK4, PRK1, PRK2,	This construct refers to the ability to comprehend and assimilate knowledge relevant to ERP, measured through six indicators. These include general (PRK1) as well as specific knowledge (PRK2) on ERP systems, awareness of the consulting firm's reputation (CONK1), knowledge of individual ERP consultant (CONK2), familiarity with ERP consultants' professional achievements (CONK3), and understanding of the after-sales service (CONK4).
AC2	EFF1, EFF2, EFF3, EFF4, EFF5, EFF6, EFF7	This construct evaluates an individual's ability to integrate ERP system knowledge effectively. The first four indicators (EFF 1, 2, 3, 4) assess confidence levels related to the practical usage of ERP systems. Additional indicators (EFF 5, 6, 7) focus on specific computer software competencies which are confidence in self-competency, ability to complete tasks, and self-judgment on proficiency with the systems.
AC3	ACAP1, ACAP2, SCAP1, SCAP2, SCAP3	The third component of absorptive capacity is measured using six indicators that assess the utilization and dissemination of ERP knowledge. ACAP1 and ACAP2 focus on the ability to apply ERP knowledge across various job roles and adapt these processes. The subsequent indicators, SCAP1, SCAP2, and SCAP3, evaluate the capacity to teach ERP usage to other colleagues.
PER	PER1, PER2, PER3, PER4, PER5	The construct of ERP usage performance based on previous study that explores the relationship between absorptive capacity and individual performance. These measures assess several aspects of ERP's impact on work performance including job performance improvement, enhancements in job productivity, increases in task speed, ask completion, and overall user satisfaction with the ERP system.

Constructs and Indicators of Absorptive Capacity

The three absorptive capacity constructs used in this study are based on prior academic work, ensuring they have been empirically tested to explore the correlation between absorptive capacity and ERP usage performance (Park et al., 2007).

The first absorptive capacity construct, which measures comprehension of ERP Systems (AC1), is quantified using six indicators. The initial measurement focuses on general knowledge (PRK1), whereas the subsequent measurement assesses knowledge (PRK2) related to ERP systems (Cohen & Levinthal, 1990; Park et al., 2007). Because prior knowledge was also deemed a crucial element, The questionnaire includes four questions about the respondents' pre-existing perceptions of ERP consulting firms and individual consultants (Park et al., 2007; Parry & Graves, 2008). Initially, it queries respondents about their awareness of the overall reputation of the ERP consulting firm before it started collaborating with their organization (CONK1). Secondly, the questionnaire explores the prior knowledge concerning the reputation of individual ERP consultants from the vendor before their involvement in ERP projects within the respondent's organization (CONK2). Furthermore, it delves into the respondents' familiarity with professional accomplishments of ERP consultants before they undertook an ERP project for the organization (CONK3). Lastly, it examines the pre-adoption awareness of the after-sales service offered by the ERP consulting firm (CONK4).

Evaluating the second absorptive capacity (AC2) component involves seven indicators (Park et al., 2007). These indicators are based on self-efficacy, which indicates individual judgment on his or her ability to perform given actions (Park et al., 2007; Schunk, 1991). Self-efficacy, which requires

individuals to monitor their performance and assess their progress, is crucial as those who believe in their capabilities generally perform better than those who doubt themselves (Compeau & Higgins, 1995; Park et al., 2007; Schunk, 1991). Four items (EFF 1, 2, 3, 4) were chosen, and these items are based on the level of confidence in individuals to use computers (Park et al., 2007). The first item (EFF1) evaluates the effectiveness perceived by users when they have access to manual, the second item (EFF2) measures confidence in problem-solving when getting support from others, the third item (EFF3) evaluates help needed in starting the system, and the fourth item (EFF4) explores respondent confidence related to available time to learn the ERP system. Meanwhile, three additional items (EFF 5, 6, 7) were designed to assess individual ability to successfully perform tasks related to developing computer software competencies (Gist et al., 1989; Park et al., 2007). The fifth item (EFF5) measures individual confidence in qualification to use ERP, the sixth item (EFF6) measures each individual confidence related to the capability to complete tasks using ERP, and the seventh item (EFF7) measures individual judgment on ERP understanding and proficiency.

This study also incorporates five additional indicators to assess the third component of absorptive capacity, namely applying ERP Systems (AC3) (Park et al., 2007). These are split into two categories: applying ERP knowledge and skills in broader job contexts and disseminating this knowledge within and outside the organization (Park et al., 2007). The first two items, ACAP1 and ACAP2 assess the individual's ability to transfer the knowledge and processes learned from ERP systems to other job roles. ACAP1 focuses on applying ERP-derived knowledge to different job scenarios, while ACAP2 evaluates the adaptability of knowledge of ERP processes in work contexts. The remaining three items, SCAP1, SCAP2, and SCAP3, explore the participants' capability to teach ERP usage to others. SCAP1 assesses the ability to instruct colleagues within the same department, reflecting intra-departmental knowledge sharing. SCAP2 extends this to inter-departmental training, thereby examining the flow of ERP knowledge across different organizational units. Lastly, SCAP3 evaluates the capacity to teach ERP systems to users from different companies, providing insights into the external dissemination of ERP expertise.

Constructs and Indicators of Performance of ERP Usage

The indicators for measuring ERP performance are derived from Park's questionnaire to measure the association between absorptive ability and individual user performance in South Korean organizations (Park et al., 2007). The criteria used to assess ERP performance are developed using DeLone and McLean's Information Systems success model, complemented by additional insights from ERP literature (Zhang et al., 2005). However, the questionnaire relies only on individual impact and user satisfaction from the DeLone and McLean model as metrics to evaluate ERP usage performance, as this study focuses on measuring individual impact. The indicators are the degree of improvement in job performance (PER1), enhancement of job productivity (PER2), increase in task speed (PER3), and facilitation of task completion (PER4). Meanwhile, the fifth degree (PER 5) focuses on the overall satisfaction of ERP systems.

Hypothesis

Previous studies have written about the positive and substantial correlation between performance using ERP systems and stages of absorptive capacity (Kwahk et al., 2020; Park et al., 2007; Saraf et al., 2013). Therefore, the actions that individuals take based on their ability to understand and apply ERP systems, such as sharing knowledge about ERP systems, developing expertise through knowledge sharing, and effectively using this expertise in their job tasks, can positively impact the utilization performance of ERP systems by advocating ERP system usage in a practical and beneficial manner (Kwahk et al., 2020). These prior research findings have led to formulating research hypotheses that describe correlations between ERP usage performance and three elements of individual absorptive capacity.

The first hypothesis is derived from prior research that demonstrated that existing knowledge positively impacts the acceptance and implementation of new technology (Park et al., 2007). Moreover, the past knowledge of organization members was significantly correlated with their comprehension of novel

and pertinent information (Park et al., 2007). Hence, the first hypothesis posits that their preexisting knowledge or comprehension of ERP systems facilitates individuals' work performance.

- Hypothesis 1: PT ABC employees' ability to understand ERP systems positively influences their performance in using ERP.

In the context of assimilating large-scale ERP systems, the concept of absorptive capacity encompasses all related processes, excluding transformation (Nandi & Vakkayil, 2018). Furthermore, the process of effective assimilation could culminate in users improving their task performance by combining their existing knowledge with newly acquired skills (Park et al., 2007). Prior studies on information systems have also highlighted the significance of the assimilation phase in enhancing system utilization (Park et al., 2007). This statement presents the second hypothesis of the study.

- Hypothesis 2: PT ABC employees' ability to assimilate ERP systems on their task positively influences their performance in using ERP.

The user's absorptive ability not only enhances existing capabilities but also applying the development of new ones (Park et al., 2007). This is accomplished by efficiently incorporating recently acquired knowledge into daily work, allowing people in the organization to establish new habits and carry out duties more effectively with this knowledge (Lee et al., 2018; Park et al., 2007). Hence, overall ability to apply knowledge can leads to improvement of ERP usage. Consequently, the third hypothesis is presented below.

- Hypothesis 3: PT ABC employees' ability to apply knowledge of ERP positively influences their performance in using ERP.

Suh & Yang's publication also shows that applying ERP Systems absorptive systems comprehension is necessary before each user internalizes the ERP knowledge into his or her task and applies the knowledge of ERP systems (Park et al., 2007). This is consistent with the organizational citizenship behavior (OCB) concept, which states that individual behavior not immediately acknowledged by the formal system often leads to organizational learning (Haryanti & Subriadi, 2021). In addition, the significance of existing knowledge is crucial for the process of assimilation, and this emphasis is clearly observed in IT assimilations in general (Nandi & Vakkayil, 2018). To be more precise, broader application and assimilation can be achieved by adopting best practices from previous experience (Nandi & Vakkayil, 2018). Consequently, the fourth hypothesis arises in this study.

- Hypothesis 4: PT ABC employees' ability to understand ERP systems positively affects their ability to assimilate ERP systems to their tasks.

According to Park et al. (2007), Zahra and George's hypothesis on absorptive capacity states that the acquisition and absorption of knowledge, referred to as 'potential' absorptive capacity, has a beneficial impact on the ability to effectively use this knowledge, known as 'realized' absorptive capacity. Undoubtedly, the process of learning knowledge inherently requires a methodical approach to effectively apply and assimilate new information (Kwahk et al., 2020). Consequently, the fifth and sixth hypotheses of this investigation are derived.

- Hypothesis 5: PT ABC employees' ability to understand ERP systems positively affects their ability to apply ERP systems to their tasks.
- Hypothesis 6: PT ABC employees' ability to assimilate ERP systems positively affects their ability to apply ERP systems to their tasks.

Data Collection

The survey was circulated among employees of the transportation company being studied. The target participants are employees who use ERP modules in their regular jobs, regardless of their professional level or department/division. The ERP modules are financial & controlling, human resources, commerce aero, commerce non-aero, and operation. This questionnaire was sent over two weeks in April 2024, and 25 respondents filled it out. The reliability and validity of this collected data will be assessed through multiple criteria in PLS-SEM, such as reflective indicator loading, AVE, HTMT,

multicollinearity, and R^2. These rigorous assessments ensure the findings are reliable and accurately reflect the underlying theoretical constructs despite the smaller sample size.

Measurement

This research project employed a closed questionnaire to evaluate hypotheses and address the research model. This study's questionnaire utilized a scale consisting of seven Likert points and adopted the instrument previously used in another study (Park et al., 2007). The researchers employed a seven-level Likert scale to score the indicator variable items, with 1 representing "completely disagree" and 7 representing "absolutely agree" study (Kwahk et al., 2020; Park et al., 2007; Xie et al., 2018).

Result

This investigation was evaluated using PLS-SEM. This model was employed because of the two levels of variables. The first-level variables consist of three constructs: understanding ERP systems (AC1), assimilating ERP systems (AC2), applying ERP systems (AC3), and performance of ERP usage (PER). Each construct is measured using multiple second-level variables, the observable indicators explained in the previous chapter. This setup dictates causality runs from the construct to its indicators because the constructs are viewed as causing the indicator variables (Hair et al., 2019). This relationship exemplifies the reflective measurement model. The analysis, including tests for reliability, validity, and hypothesis evaluation, was conducted using SmartPLS 4.0.

Evaluating Reflective Measurement Model

Assessing the reflective measurement model in PLS-SEM is foundational to guarantee the dependability and accuracy of the research results (Hair et al., 2017b; Hair et al., 2019). It sets the stage for robust hypothesis testing by ensuring the constructs are well-defined and reliable, thereby enhancing the overall quality and credibility of the research.

The first step in assessing reflective measurement models is to examine indicator loading. The results are displayed in Table 1, where each indicator exhibits loadings above 0.708. This result shows solid and reliable relationships between constructs and their indicators, meaning that an indicator correlates well with the construct it represents and implies a construct' reliable measure (Hair et al., 2019).

The second phase involves evaluating the internal consistency reliability of the indicators to ensure that all indicators measure the same underlying intended construct and thus reflect the same latent variable (Aburumman et al., 2023; Hair et al., 2019). The internal consistency reliability was evaluated by employing Cronbach's alpha and composite reliability (ρ_A and ρ_C) (Hair et al., 2019). Table 2 reports the consistency reliability results across constructs AC1, AC2, AC3, and PER. The findings reveal that Cronbach's alpha for each construct exceeds the 0.7 threshold, suggesting coherence among the indicators intended to measure the same constructs (Aburumman et al., 2023; Hair et al., 2019). Similarly, composite reliability measures, including ρA and ρC, also exceed 0.7 for all constructs, affirming that the constructs are reliable and provide a consistent representation of the theoretical structures they are intended to measure (Aburumman et al., 2023; Hair et al., 2019).

The following step assesses convergent validity using each construct's average variance extracted (AVE) (Hair et al., 2019). Convergent validity refers to the extent to which numerous items accurately measure the same underlying concept and align with each other (Aburumman et al., 2023; Hair et al., 2019). It describes how the measure of a construct captures the amount of variance from its indicators compared to the variance caused by measurement error (Aburumman et al., 2023; Hair et al., 2019). Table 3 displays the outcome of the AVE analysis. All constructs have an AVE value that exceeds 0.50. This suggests that all indicators are good measures of the related construct, supporting the model's convergent validity (Hair et al., 2019).

Table 2. Indicator Loading Test Result

Indicator	Constructs			
	AC1	AC2	AC3	PER
PRK1	0.789			
PRK2	0.841			
CONK1	0.836			
CONK2	0.858			
CONK3	0.895			
CONK4	0.948			
EFF1		0.895		
EFF2		0.835		
EFF3		0.833		
EFF4		0.901		
EFF5		0.923		
EFF6		0.953		
EFF7		0.889		
ACAP1			0.928	
ACAP2			0.872	
SCAP1			0.812	
SCAP2			0.936	
SCAP3			0.806	
PER1				0.827
PER2				0.890
PER3				0.852
PER4				0.934
PER5				0.891

Table 3. Indicator Loading Test Result

Constructs	Cronbach's alpha	Composite reliability (ρ_A)	Composite reliability (ρ_C)	Average variance extracted (AVE)
AC1	0.930	0.940	0.946	0.744
AC2	0.956	0.958	0.964	0.793
AC3	0.921	0.931	0.941	0.761
PER	0.927	0.930	0.945	0.774

When evaluating reflective measurement models in PLS-SEM, the last stage typically involves measuring discriminant validity through the heterotrait-monotrait (HTMT) ratio (Hair et al., 2019). In research using PLS-SEM, Discriminant validity serves to confirm that each construct within the model uniquely captures and represents different theoretical concepts, ensuring they are statistically distinct from each other (Aburumman et al., 2023). According to the results presented in Table 4, the HTMT values of constructs used in this research are less than 0.85. This finding suggests that each construct in

a model reflects a distinct element that independently contributes to the understanding of the components under investigation.

Table 4. Discriminant Validity Test Result

Constructs	AC1	AC2	AC3	PER
AC1				
AC2	0.680			
AC3	0.642	0.834		
PER	0.685	0.780	0.876	

Evaluating Structural Model

Following the successful evaluation of the measurement model, the next phase in evaluating the research is examination of structural model. This assessment examines the relationships between the constructs within the theoretical framework of this study (Hair et al., 2019). The main objective to evaluate the structural model in PLS-SEM is to verify the proposed hypotheses between constructs (Hair et al., 2017b; Hair et al., 2019). The primary assessment parameters that should be considered are the coefficient of determination (R^2) and the statistics of the path coefficient (hypothesis testing) (Hair et al., 2019; Mayeh et al., 2016). However, to avoid any potential distortion of the coefficients between constructs, it is crucial to analyze collinearity by employing variance inflation factors (VIF) (Hair et al., 2019). This preliminary step helps prevent inaccuracies in interpreting the relationships within the model.

Table 5 shows the VIF values for all constructs. All values are close to or below 3, which indicates no significant multicollinearity among the constructs (Hair et al., 2019). Therefore, the structural model analysis may confidently proceed, as each construct provides distinct and significant information to the model without duplicating information from other constructs.

Table 5. VIF Values

Constructs	AC1	AC2	AC3	PER
AC1		1.000	1.714	1.786
AC2			1.714	3.012
AC3				2.762
PER				

The next step is assessing the R^2 value of constructs explained or predicted in the model by other latent variables, called endogenous construct. The endogenous constructs in this research consist of AC2, AC3, and PER. The SMART PLS analysis reveals that the R^2 value for AC2 is 0.417, for AC3 is 0.638, and for PER is 0.712. The R^2 value of AC2 suggests a moderate explanatory power, which means 41,7% of AC2 is influenced by AC1. Meanwhile, the R^2 values of AC3 and PER are 0.638 and 0.712 each, which means the model effectively captures the factors influencing AC3 and PER. It also means that AC1 and AC2 influence 63.8% of AC3, while AC1, AC2, and AC2 influence 71,2% of PER. These show moderate and strong results between constructs and substantially explain dependent constructs (Hair et al., 2019; Mayeh et al., 2016).

After evaluating the VIF and R^2 values, the next step is to examine the path coefficients between constructs to validate the research's hypothesis. The evaluation of path coefficients involves a two-step process (Aburumman et al., 2023). The initial step requires verifying that the p-values are below the conventional threshold of 0.05 (Aburumman et al., 2023). This criterion implies that the effects are statistically significant and unlikely to be attributed to random chance. The second step is the examination of the confidence intervals for these path coefficients (Aburumman et al., 2023). This

means that if the path coefficient's confidence interval excludes the value zero, it indicates significant statistical support for the hypothesized relationship.

Table 6. Result of Hypothesis (Path Coefficient) Testing

Hypothesis	Path	Path Coefficient	P-Value	Confidence Interval		Decision
				Lower Level	Upper Level	
H1	AC1 → PER	0.182	0.334	-0.209	0.538	Not Supported
H2	AC2 → PER	0.172	0.514	-0.437	0.559	Not Supported
H3	AC3 → PER	0.573	0.004	0.164	0.971	Supported
H4	AC1 → AC2	0.646	0.000	0.400	0.798	Supported
H5	AC1 → AC3	0.161	0.400	-0.275	0.468	Not Supported
H6	AC2 → AC3	0.685	0.000	0.337	1.008	Supported

The path coefficient analysis findings are depicted in Figure 2 and Table 6. Figure 2 depicts the path coefficients and their corresponding p-values across different constructs. Meanwhile, Table 6 elaborates on these findings by including confidence intervals and evaluative decisions for each hypothesis in this investigation. The results indicate that Hypothesis 1 is rejected because the p-value of 0.334 is higher than the accepted significance threshold, and the confidence interval includes zero. Similarly, Hypotheses 2 and 5 are unsupported as their p-values also surpassed 0.05, and their confidence interval crosses zero. In contrast, Hypotheses 3, 4, and 6 are supported since each demonstrates p-values below the 0.05 threshold, and the confidence interval range doesn't cross zero. These indicate significant support for hypotheses 3, 4, and 6 within the research model.

Figure 2. PLS Model of Relationships between AC1, AC2, AC3 and PER

This nuanced influence is systematically detailed in Table 7, which provides calculated direct and indirect impacts of all endogenous constructs as analyzed via SmartPLS. Table 7 shows indirect effects can have a more substantial impact than direct effects, specifically on PER. It highlights the importance of considering the broader network of relationships within the model to fully understand the dynamics

of implementing and utilizing ERP systems. Additionally, the confidence interval for each indirect path does not include zero, indicating robust statistical support for these relationships.

Table 7. Total Effects on Endogenous Constructs

Path	Total Effect	Confidence Intervals	
		Lower Level	Upper Level
AC1 → PER	0.639	0.321	0.802
AC2 → PER	0.565	0.337	1.008
AC3 → PER	0.573	0.164	0.971
AC1 → AC2	0.646	0.400	0.798
AC1 → AC3	0.603	0.236	0.763
AC2 → AC3	0.685	0.337	1.008

Discussion

Drawing from a case study on PT ABC, this study examines the correlation between the absorptive capacity of ERP users and their performance in using ERP. It also seeks to enhance comprehension of the dynamics between the absorptive capacity of ERP users and successful ERP adoption. This study's findings also enhance the field of enterprise information systems by adding to the existing literature on ERP and expanding beyond the typically studied areas of planning and implementation phases (Zhu et al., 2010). Even though interest grows in the other phases, notably the operation and enhancement phases (Shaul & Tauber, 2013), Prior publications still focus on success criteria (Esteves & Pastor, 2001; Hasan et al., 2019; Zhu et al., 2010).

Theoretical Implications

This research findings highlight that while the absorptive capacity of the application of ERP systems knowledge (AC3) directly and positively influences ERP performance (PER), the capacities related to understanding (AC1) and assimilating (AC2) ERP systems do not directly impact performance outcomes (PER). Nonetheless, these outcomes should not be seen as contradicting the finding on the influence of absorptive capacity based on previous research, as the indirect influences of these constructs continue to positively affect ERP usage. Notably, Prior comprehension of ERP Systems (AC1) emerges as the most influential construct on PER with a total effect value of 0.639, underscoring its pivotal role in enhancing ERP performance. This indirect influence underscores the importance of initial knowledge acquisition as a precursor to effective application and innovation within ERP systems, corroborating Lee et al.'s assertion that knowledge acquisition is critical before being effectively utilized and integrated into operations to enhance performance (Park et al., 2007). Further analysis also demonstrates the capacity to assimilate ERP systems (AC2) indirectly contributes to performance (PER) by enhancing the application of ERP systems (AC3) with a total effect value of 0.565.

Because AC3, the sole construct directly and positively influencing ERP usage performance, is assessed using six indicators that evaluate the dissemination of ERP knowledge inside and outside the organization. The positive contribution of AC3 highlights that activities focused on knowledge transfer and learning in the organization can effectively enhance ERP systems usage. These outcomes support the research by Lee et al. (Lee et al., 2018), which indicates that organizational coordination capabilities, including participation and cross-functional activities, significantly boost a firm's ability to absorb new capabilities. Furthermore, this result aligns with Jansen et al.'s findings, which suggest that enhancing socialization capabilities—such as socialization tactics and connectedness—can also improve a firm's absorptive capacities (Jansen et al., 2005).

This study provides an in-depth account of the previous research carried out by Kwahk et al. While Kwahk's study focuses solely on the beneficial influence of overall absorptive ability on ERP usage performance (Kwahk et al., 2020), This study demonstrates a clear and indirect positive correlation

between each component of individual absorptive capacity. The findings of this paper also largely support the previous findings of Park et al., which suggest the positive and direct impact of behavior in assimilating and applying ERP systems knowledge to ERP systems usage performance (Park et al., 2007). However, this study offers a nuanced perspective by revealing that applying ERP systems has an indirect beneficial effect on the performance of ERP usage. This research also illustrates favorable direct and indirect correlations between the elements of potential and realized absorptive capacity, examining the interactions between these components through empirical analysis. Potential absorptive capacity refers to the ability to acquire and assimilate knowledge, whereas realized absorptive capacity involves applying, exploiting, or transforming ERP knowledge (Zahra & George, 2002).

The results of this study partially support Mayeh et al.'s (2016) previous findings, indicating a positive and direct influence of absorptive capacity on ERP system usage performance. This study also uncovers indirect relationships between absorptive capacity and ERP usage performance, factors that were not measured in Mayeh et al.'s (2016) study.

Practical Implications

This study offers practical recommendations for PT ABC to refine its ERP adoption strategies. First, PT ABC must influence the behavior of individuals in every facet of absorptive capacity. This approach is critical because the success of an organization and its behavioral dynamics are rooted in the absorptive capacity of individual employees (Park et al., 2007). This also aligns with conceptualization of absorptive capacity, which posits that the capacity of an organization to assimilate and apply external knowledge fundamentally depends on the collective absorptive capacities of its workforce (Cohen & Levinthal, 1990; Nandi & Vakkayil, 2018).

The finding that prior knowledge of ERP is the most significant factor necessitates that PT ABC Management proactively encourages employee participation in developing expertise and obtaining new insights before ERP adoption. This engagement could be facilitated through participation in external workshops and training sessions conducted by third parties, covering critical ERP aspects such as system integration, administration, and development. Essential elements of such a culture include a collaborative environment, mutual trust, and an atmosphere devoid of competition, where individuals are more likely to share knowledge freely, including information directly related to projects (Lee et al., 2018). To nurture this environment, corporate leaders should promote a clan-oriented culture that facilitates the organization's transformation and effective utilization of knowledge (Lee et al., 2018). Additionally, the transfer of expertise could be enhanced by employing seasoned consultants who can aid in understanding and answering pertinent inquiries during the implementation (Aloini et al., 2007). By adopting such strategies, PT ABC will be able to ensure that its workforce is adequately trained and acquire a thorough comprehension of the ERP system before its implementation and subsequent rollout.

The knowledge management for this collaborative behavior can be conducted formally or informally, referred to as codification or personalization strategies (Parry & Graves, 2008; Woods & Cortada, 2013). The codification strategy is predominantly targeted at IT and implementation project teams, while the personalization strategy is aimed at end users (Parry & Graves, 2008; Woods & Cortada, 2013). To codify knowledge, organizations document all processes, lessons learned, and guidance notes at the conclusion of each ERP project and then store these documents in an openly accessible library (Parry & Graves, 2008). The knowledge from the codification strategy is stored in standard repositories used and accessed by the organization. Conversely, the approach of personalization strategy for exchanging tacit knowledge within the organization largely relies on informal knowledge transfer methods and on-the-job training (Parry & Graves, 2008). Knowledge management under the personalization strategy is primarily the responsibility of functional managers, meaning system knowledge tends to be concentrated at the unit or department level rather than being disseminated across the entire organization (Parry & Graves, 2008).

Conclusions

This study sought to assess the impact of three dimensions of workers' absorptive capacity on their proficiency in using ERP systems at PT ABC. The study utilized a theoretical model based on Park et

al (2007) framework and implemented PLS-SEM analysis using SmartPLS software. The findings indicated that out of the three aspects of individual absorptive capacity, only the capacity specifically connected to applying knowledge of ERP systems directly improves performance in using ERP systems. On the other hand, the capacity to understand and assimilate ERP knowledge has a noteworthy indirect influence on the effectiveness of using ERP. This highlights the intricate interaction of various absorptive capabilities in maximizing the utilization of ERP systems.

Based on these insights, PT ABC is recommended to develop strategies to modify individual employee behaviors to maximize their absorptive capacities. This involves actively fostering employee engagement to acquire relevant expertise and insights prior to ERP system adoption. Participation in external workshops and training sessions could serve as an effective method to encourage such involvement. Moreover, promoting behaviors that facilitate the sharing of ERP-related information and fostering collaborative knowledge sharing is essential for enhancing the effective and beneficial use of ERP systems. This research also underscores the importance of cultivating an organizational culture characterized by collaboration, mutual trust, and a non-competitive atmosphere. Such a culture enhances the collective ability to utilize ERP systems effectively, thereby potentially improving overall organizational productivity and efficiency. Implementing these strategic initiatives is anticipated to significantly enhance PT ABC's ERP adoption plan, aligning with the company's broader objectives of improving operational efficiency and productivity.

Limitations

This research provides valuable insights yet is constrained by several limitations. First, the study's relatively small sample size of 25 respondents is modest compared to prior studies employing similar structural models. Despite thorough analyses to validate the sample and instrument, a larger sample would likely strengthen the statistical robustness and validity of the conclusions and hypotheses. Furthermore, the scope of the study, restricted to a single company in Indonesia, may limit the generalizability of the findings. This presents an opportunity for future research to include a more diverse array of organizations across different sectors, enhancing understanding of industry-specific traits and demands within the region.

Additionally, the analysis focuses exclusively on a company that has successfully implemented the SAP program, although ERP solutions encompass a variety of platforms beyond SAP. Future research could include different ERP systems, providing a more comprehensive view of ERP deployment and utilization. Lastly, the study does not explore potential moderating factors impacting ERP adoption outcomes, such as the intention to use ERP and organizational support. Future studies can include new constructs or examine moderating effects. It might reveal significant contrasts and provide deeper insights into ERP usage and implementation dynamics.

References and Citations

Aburumman, O. J., Omar, K., Al Shbail, M., & Aldoghan, M. (2023). How to Deal with the Results of PLS-SEM? *Lecture Notes in Networks and Systems*, *495 LNNS*, 1196–1206.

Aloini, D., Dulmin, R., & Mininno, V. (2007). Risk management in ERP project introduction: Review of the literature. *Information & Management*, *44*(6), 547–567.

Boynton, A. C., Zmud, R. W., & Jacobs, G. C. (1994). The influence of IT management practice on IT use in large organizations. *MIS Quarterly: Management Information Systems*, *18*(3), 299 – 316.

Chang, H.-H., Chou, H.-W., Yin, C.-P., Lin, C. I., Chang, H.-H. :, Chou, H.-W. :, Yin, C.-P., & Lin, C. (2011). ERP Post-Implementation Learning, ERP Usage and Individual Performance Impact. *Proceedings of PACIS 2011*. http://aisel.aisnet.org/pacis2011/35

Chang, J. (2024, March 27). *90 Vital ERP Software Statistics 2024: Data Analysis & Market Share*. FinancesOnline. https://financesonline.com/erp-software-statistics/

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128-152.

Compeau, D. R., & Higgins, C. A. (1995). Application of Social Cognitive Theory to Training for Computer Skills. *Information Systems Research*, *6*(2), 118-143.

Esteves, J., & Pastor, J. (2001). Enterprise Resource Planning Systems Research: An Annotated Bibliography. *Communications of the Association for Information Systems*, *7*.

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology*, *74*(6), 884–891.

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems*, *117*(3), 442–458.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Hallikainen, P., & Seethamraju, R. (2015). Aligning enterprise systems with the organisation – A sensemaking perspective. *ACIS 2015 Proceedings - 26th Australasian Conference on Information Systems*.

Haryanti, T., & Subriadi, A. P. (2021). Review of semantic Absorptive Capacity (AC) in information system research. *Procedia Computer Science*, *197*, 92–101.

Hasan, N., Miah, S. J., Bao, Y., & Hoque, M. R. (2019). Factors affecting post-implementation success of enterprise resource planning systems: a perspective of business process performance. *Enterprise Information Systems*, *13*(9), 1217–1244.

Hsu, P. F., Yen, H. J. R., & Chung, J. C. (2015). Assessing ERP post-implementation success at the individual level: Revisiting the role of service quality. *Information and Management*, *52*(8), 925–942.

Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2005). Managing Potential and Realized Absorptive Capacity: How do Organizational Antecedents Matter? *Academy of Management Journal*, *48*(6), 999–1015.

Kwahk, K. Y., Yang, S. B., & Ahn, H. (2020). How organizational citizenship behavior affects ERP usage performance: The mediating effect of absorptive capacity. *Sustainability (Switzerland)*, *12*(11).

Lee, J. C., Hsu, W. C., & Chen, C. Y. (2018). Impact of absorptive capability on software process improvement and firm performance. *Information Technology and Management*, *19*(1), 21–35.

Mata, M. N., Martins, J. M., & Inácio, P. L. (2023). Impact of absorptive capacity on project success through mediating role of strategic agility: Project complexity as a moderator. Journal of Innovation and Knowledge, 8(1).

Mayeh, M., Ramayah, T., & Mishra, A. (2016). The role of absorptive capacity, communication and trust in ERP adoption. *Journal of Systems and Software*, *119*, 58–69.

Nandi, M. L., & Vakkayil, J. (2018). Absorptive capacity and ERP assimilation: the influence of company ownership. *Business Process Management Journal*, *24*(3), 695–715.

Park, J.-H., Suh, H.-J., & Yang, H.-D. (2007). Perceived absorptive capacity of individual users in performance of Enterprise Resource Planning (ERP) usage: The case for Korean firms. *Information and Management*, *44*(3), 300 – 312.

Parry, G., & Graves, A. (2008). The importance of knowledge management for ERP systems. *International Journal of Logistics: Research and Applications*, *11*(6), 427–441.

Ramadhan, A., Iyiola, K., & Alzubi, A. B. (2024). Linking absorptive capacity to project success via mediating role of customer knowledge management capability: the role of environmental complexity. *Business Process Management Journal*.

Saraf, N., Liang, H., Xue, Y., & Hu, Q. (2013). How does organisational absorptive capacity matter in the assimilation of enterprise information systems? *Information Systems Journal*, *23*(3), 245–267.

Schunk, D. H. (1991). Self-Efficacy and Academic Motivation. *Educational Psychologist*, *26*(3), 207–231.

Sharma, S., Daniel, E. M., & Gray, C. (2012). Absorptive Capacity and ERP Implementation in Indian Medium-sized Firms. *Journal of Global Information Management (JGIM)*, 54–79.

Shaul, L., & Tauber, D. (2013). Critical success factors in enterprise resource planning systems: Review of the last decade. *ACM Computing Surveys*, *45*(4).

Statista. (2024, March 27). *Enterprise Resource Planning Software - Indonesia*. Statista. https://www.statista.com/outlook/tmo/software/enterprise-software/enterprise-resource-planning-software/indonesia

Uddin, M. A., Alam, M. S., Mamun, A. Al, Khan, T. U. Z., & Akter, A. (2020). A Study of the Adoption and Implementation of Enterprise Resource Planning (ERP): Identification of Moderators and Mediator. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(1), 2.

Wang, E. T. G., Chia-Lin Lin, C., Jiang, J. J., & Klein, G. (2007). Improving Enterprise Resource Planning (ERP) Fit to Organizational Process Through Knowledge Transfer. *International Journal of Information Management*, *27*(3), 200–212.

Woods, J. A., & Cortada, J. (2013). What's your Strategy for Managing Knowledge? *The Knowledge Management Yearbook 2000-2001*, 55–69.

Xie, X., Zou, H., & Qi, G. (2018). Knowledge absorptive capacity and innovation performance in high-tech companies: A multi-mediating analysis. *Journal of Business Research*, *88*, 289–297.

Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization, and Extension. *Academy of Management Review*, *27*(2), 185–203.

Zhang, Z., Lee, M. K. O., Huang, P., Zhang, L., & Huang, X. (2005). A framework of ERP systems implementation success in China: An empirical study. *International Journal of Production Economics*, *98*(1), 56–80.

Zhu, Y., Li, Y., Wang, W., & Chen, J. (2010). What leads to post-implementation success of ERP? An empirical study of the Chinese retail industry. *International Journal of Information Management*, *30*(3), 265–276.

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A Data-Driven Approach for Game Evaluation Using Latent Dirichlet Allocation Method Based on Players' Reviews

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Abstract

Garena is a global game developer and publisher. Garena provides users with access to popular and engaging online games for mobile and PC, developed, curated, and localized for each market. The Battle Royale genre is relatively new, and this research will evaluate Free Fire, one of the games in this genre made by Garena. Analyzing end-user reviews is considered important for evaluating software quality. Researchers need to understand which aspects need to be evaluated based on player reviews on Google Play and how the model's performance is generated using feedback from players who have played Free Fire. In this study, researchers use the Latent Dirichlet Allocation (LDA) method to model topics and generate clusters in discussions for each topic. LDA is a generative probabilistic model of a corpus. This research on topic modeling using Google Play reviews and LDA has identified the topics users are most concerned with. The research shows three main aspects: bugs, graphics and performance, and game rules/punishment policy, as aspects that need to be evaluated based on player reviews on Google Play.

Keywords: LDA, Garena, Data Mining, Gameplay, Free Fire, Google Play, Review, Topic Modeling.

Introduction

J.P. Morgan, in their report, said the lifecycle of games in the battle royale genre is relatively new and hard to evaluate. One way to evaluate the playability of a video game product is through the opinions of game players. Reviews are considered important for software quality evaluation (Sharma, 2019). One way of evaluating the playability of video game product is through opinions of the game players. Players give their opinions, feedback, and suggestions through the Google Play Store, its publication

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platform on Android. Google Play has a valuation feature that allows customers to give reviews on the advantages and disadvantages of using an app (Hermanto et al., 2020).

Garena is part of Sea integrated platform that provides services of many popular online mobile and PC games that are localized to each region (Sea Limited, 2021). Figure 1 depicts three Garena's core business areas: esports, games, and communities. Free Fire is one of the games being self-developed by Garena and it's one of the most successful in terms of revenue. According to the report, in several region, Free Fire has been topping the app store rank from March 2019 until June 2019 (Sharma, 2019).

Figure 1. Garena Core Business Area

Kwak et al (2020) identify critical topics for successful games in game reviews by using topic modeling analysis. Kwak et al (2020) used LDA to find 50 topics by crawling data from the game review site (www.metacritic.com/game). On the other hand, there is similar research from Lin et al. using multi-label text classification (MLTC) algorithms. The data evaluated were game reviews of Steam games. The research maps the result to three dimensions of playability: functionality, gameplay, and usability (Lin et al., 2019). The results showed that a review-data-driven method can effectively evaluate the perceived quality of video games, enumerating their merits and defects in terms of playability. Furthermore, the Google Play Store is also used as a data source in research discussing sentiment analysis of Google Play reviews using the Naïve Bayes Algorithm and SVM (Hermanto et al., 2020). The research includes preprocessing methods for data before it is processed by the model. The accuracy achieved in this research is reported to be quite high.

Kwak et al (2020), Li et al (2021), and Hermanto et al (2020) did not focus their research on a specific genre of game, such as the battle royale genre. According to a J.P. Morgan report, the battle royale genre is relatively new and hard to evaluate, especially using Google Play data as a data source. This gap needs to be addressed. The goal of this research is to understand which aspects need to be evaluated based on players' reviews on Google Play. This way, Garena will understand how to evaluate the playability of their video game based on players' reviews on Google Play. The method used in this research will be topic modeling using the LDA (Latent Dirichlet Allocation) method as a topic modeling analysis technique. LDA was first introduced in 2003 and has since become the de facto standard for information retrieval. Many studies have already shown that LDA performs well in document classification (Kim & Gil, 2019; Lee & Seo, 2020; Tan, 2020).

Literature Review

Text Mining with Google Play Review

Google Play, as Google's official store for Android apps, is a significant platform with over a million downloadable applications (Fuad et al., 2020). Google Play includes a feature that allows users to view reviews left by other app users (Hossain & Rahman, 2024). User reviews are frequently used as an effective and efficient resource for gathering information about a product or service (Kim & Lee, 2023) Recent research indicates that nearly 50% of internet users depend on word-of-mouth recommendations before trying a product, as user reviews offer current information (Aaputra et al., 2019).

Customer opinions written on social media or reviews on Google Play, to a lesser extent or a lot, will impact potential customers. However, monitoring public opinions does come with challenges. Opinions posted on social media are too numerous to process manually and therefore need a proper data analysis method to gain values from it (Aaputra et al., 2019). For this reason, a special method or technique is needed to categorize these reviews automatically into one topic that generally presents these reviews.

One method used to find patterns or information is called text mining. Text mining is the process of uncovering patterns from large amounts of text data which may be unstructured or semi-structured (Cai

& Sun, 2009). Text mining usually requires input data to be processed first using a set of parsing processes and other techniques (Hermanto et al., 2020).

Topic Modelling

Topic modelling is used to determine the most dominant topic among a big amount of data (Drus & Khalid, 2022). Topic modelling can be used on unstructured data by applying various clustering methods (Maryamah et al., 2019). In other words, topic modeling is a technique that can analyze large volumes of text without using labels. This is known as unsupervised learning, and its goal is to uncover hidden topics (Negara & Andryani, 2019). Topic modelling is an example of text mining.

Previously, Vukanti & Jose (2021) has described how topic modelling works. Firstly, data is collected in a big collection of documents of unstructured texts called Corpus. Afterwards, word-topics will be extracted through topic modelling methods which will result in a topic trend. Therefore, there are two main outputs of topic modelling, a collection of topics which are the most frequently occurred words and a list of documents that are associated with similar topics. Topic generated are supposedly unique.

Among the types of most used topic modelling, there are four types (Vukanti & Jose, 2021):

1. Latent Semantic Analysis (LSA): LSA takes advantage of vector-based representation
2. Probabilistic Latent Semantic Analysis (PLSA): PLSA uses probabilistic framework to construct semantic structure of a data
3. Latent Dirichlet Allocation (LDA): LDA measures the similarity of each provided documents with the acquired distribution of all documents
4. Correlated Topic Model (CTM): CTM makes use of logistic normal distribution to retrieve topics from documents.

LDA

Latent Dirichlet Allocation (LDA) is a popular topic modeling method used to identify hidden thematic patterns within a set of documents (Nawang Sari & Dwi Purnomo, 2022). LDA assumes that every document consists of a mix of multiple topics, and each topic is characterized by a distribution of words (Chen et al., 2017). Through the application of LDA, researchers can discover these underlying topics and their distribution throughout the document corpus, facilitating a more profound comprehension of the content and themes present (Yoshida et al., 2023). A significant benefit of LDA is its capability to automatically detect topics without requiring labeled data, which proves especially valuable in situations where manual annotation is either impractical or costly (Li et al., 2015).

The processes of LDA can be summarized like this (Goyal & Kashyap, 2022). The procedure begins with specifying the number of documents as m, the number of topics as t, and the vocabulary matrix as β. These elements are essential for initiating the topic modeling process using Latent Dirichlet Allocation (LDA). Then, these steps are done:

1. Select Topic Distribution: Choose the initial distribution of topics (α).
2. Assign Topics to Words: For each word W in every document d:
    a. Decide which topic t the word belongs to.
3. Calculate Probabilities:
    a. Estimate P(Topic t | Document d): Probability of topic t given document d.
    b. Compute P(word W | Topic t): Probability of word W given topic t.
4. Select Words for Topics: Use the distribution of words in β to select the specific words associated with each topic t.

Generally, LDA analyzes a single document and various input parameters to generate a model comprising weights that can be normalized into probabilities. These probabilities fall into two categories: (a) the likelihood that a specific document generates a particular topic, and (b) the likelihood that a specific topic generates a particular word from the vocabulary set (Goyal & Kashyap, 2022).

Methodology

This study consists of several phases to obtain accurate analytical results. In this study, researchers use the Latent Dirichlet Allocation (LDA) method to model topics and generate clustering in discussions for each topic. This research uses Google Play data crawled using a Python program. There are three major phases that consist of preparation and crawling, data preprocessing, and the LDA process itself.

Google Play Preparation and Data Crawling

Preparation

In this step, we do several research to understand more about how LDA algorithm works in a python program. In this stage, we setup the environment required to run the LDA model. The platform being used is Google Colab, a product developed by Google Research which enables anybody to write and execute python codes on browser. On preparation step, external libraries installed and imported. External libraries used are google-play-scraper, pyLDAvis, and Sastrawi.

Data Crawling

After installing required library, we crawl data from google play to used. The researchers use 'com.dts.freefireth' as identifier, id as language used and id as country origin. The researchers also add 200000 as number of data crawled for this research. The results of the data crawling that was carried out produced data with the following columns: reviewId, userName, userImage, content, score, thumbsUpCount, reviewCreatedVersion, at, replyContent, and repliedAt. The researchers will use the data retrieved in this process to be processed further in the next step.

Data Preprocessing

After data crawling process, we use NLTK's library to enable stopwords in Indonesian. Stopwords are used to remove word that doesn't have any meaning by itself, such as conjunctions, prepositions, and pronouns (Gustafson et al., 2008). In addition, we also use Sastrawi library to help with the stemming process. Stemming is a text processing method used to convert words in sentence to its basic form so it would be standardized and unified (Rao & Ranjana, 2020). After adding library's stopwords. The researchers extended several stopwords to improve quality. The researchers add 34 new stopwords into data set. The additional stopwords were obtained after conducting analysis, which identified these extra words as unnecessary for this research. By using stopwords, the text emphasizes the key terms and phrases that convey the main semantic content, which enhances the accuracy of subsequent analysis tasks (Amarasinghe et al., 2015).

To focus the dataset on points that need to be improved, researchers only use data with a rating below 3. Thus, this process also includes filtering data of reviews with above condition. Furthermore, during this step, there a function that transform a string (original review) to an array of words. Inside the function, there was some steps:

1. Escape the punctuation and white spaces: Such character is not relevant for text processing; therefore, punctuation needs to be removed from the review first.
2. Stemming: Stemming needs to be done to generalize words by converting it to original form. This step returns a sentence that has its words converted to base form.
3. Tokenizing: To make the review able to be processed, it needs to be in a form of array of string. Therefore, in this step, the sentence or in other words the string itself spoilt with single white space as separator then saved to an array.
4. Removing Stop Words: Stop words doesn't hold any meaning and could potentially affects the result of topic modelling in bad ways, therefore it needs to filter from the final array.

Afterwards, each data's content column will be mapped using previous function.

Latent Dirichlet Allocation

Determine Optimum Number of Topics

During this step, we will try out the possibilities for number of topics by simulating it using LDA model that is used in this research. For every number of topics, the one with the highest performance will be used as the final number of topics and be proceeded to the next step.

Topic Modeling with Latent Dirichlet Allocation (LDA)

On this step, we generate LDA model using Gensim library. The input used to generate the LDA model were corpus, dictionary of words, and number of topics. pyLDAvis is used to help the researchers visualize the result and gain clearer picture of each topic which includes its distribution and coherence. Furthermore, the coherence scores found in this study will be compared to existing research related to topic modeling in game reviews. Previous study has indicated that the average coherence score for game review topics is 0.470 (Li et al., 2021). This comparison will help in evaluating the effectiveness and reliability of our topic models in capturing coherent and meaningful themes within the game reviews.

Topic Interpretation

In this phase, the authors draw conclusions from the results and discussions made in the previous phase. The interpretation is done with Human-In-The-Loop approach, or HITL which refers to a methodology that integrates human expertise and intervention at various stages of the machine learning process (Abdel-Karim et al., 2020). The topic interpretation will be done using a human-in-the-loop approach, where the researchers will review the sets of words generated by the LDA model and assign meaningful themes to each topic based on their contextual understanding.

For more details, methodology captured in Figure 2 below.

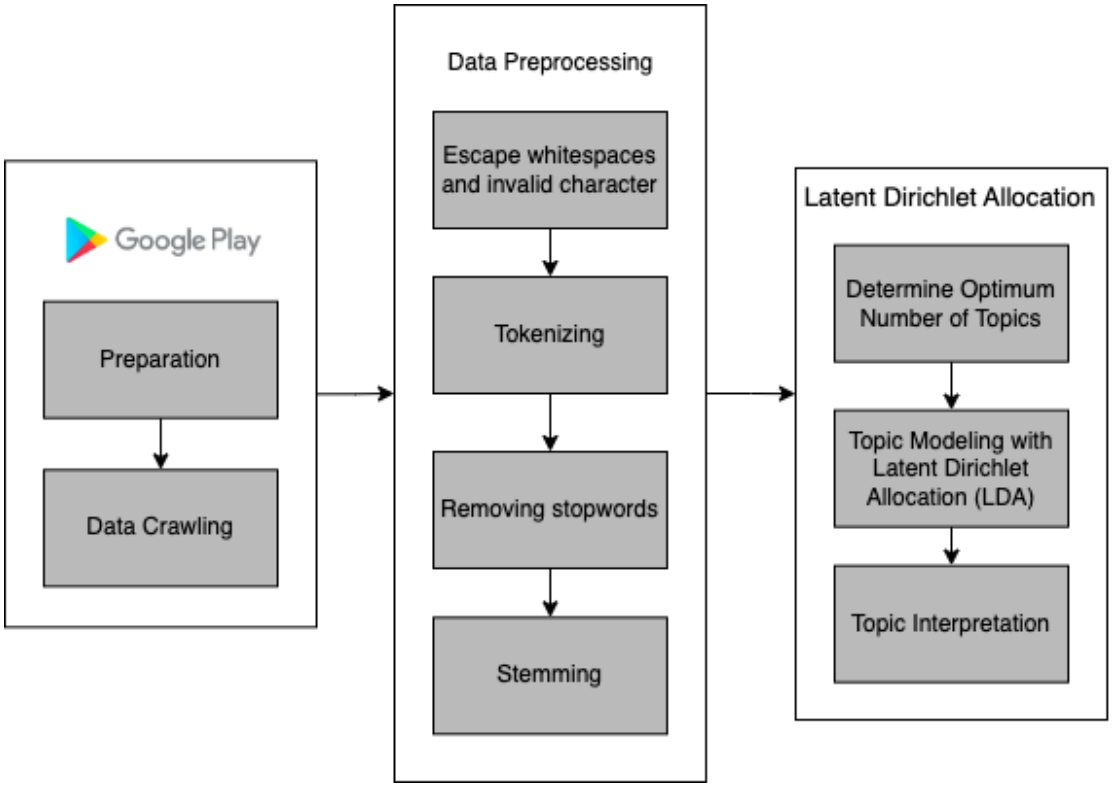

Figure 2. Methodology

Result

The process of deciding optimal number of topics is done through coherence score evaluation. Coherence scores describe how interpretable is a certain topic. Therefore, the higher the score the better because it means that detected topics are more interpretable. Figure 3 shows the result of evaluating number of topics with topic number (k) values that range from 1 until 9. The result shows that the highest score was obtained using k=3 with the value of 0.426, although six number of topics seems to be almost in par in terms of coherence score. Despite that, we have decided the number of topics used will be three because it has the highest score. Compared to previous research related to game reviews topic modeling, the coherence score is not far off from the average coherence score value retrieved, which shows a consistent level of topic coherence and suggests that our topic models are effectively capturing meaningful themes within the dataset (Li et al., 2021).

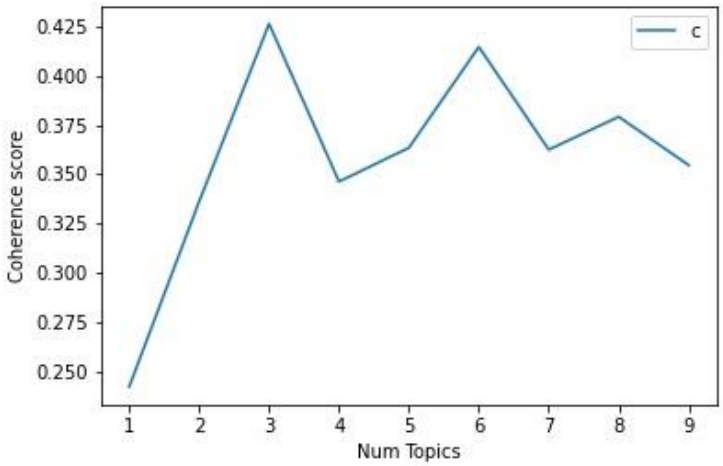

Figure 3. Number of Topics Evaluation

The result of the model using three number of topics has generated these most frequent terms. Table 1 shows the top twenty most frequent term for each topic with notes, that some of the words are being censored because it contains profanity.

Table 1. Topics and Most Frequent Term

Topic 1	Topic 2	Topic 3
garena	bu**k	ff
tolong	gem	akun
main	pintu	download
bug	hp	login
bagus	to**l	top
update	patah	up
sinyal	bit	pensi
jaring	geme	rusak
kasih	bocil	pake
free	epep	dm
fire	buruk	hapus
bintang	a**	orang

Topic 1	Topic 2	Topic 3
pas	mending	kena
jelek	mata	bang
player	bur**q	gara
mohon	grafik	lu
banget	bikin	suspend
seru	ram	main
suka	sakit	beli
masuk	ml	kaya

Discussion

The first topic can be interpreted as a complaint for player issues with bugs, as seen with words such as 'bug'. Furthermore, 'sinyal' and 'jaring' terms can be interpreted as player's inconvenience in terms of the game network performance. The same goes for 'jelek' which symbolizes some aspects of the game playability was not up to player standards or it may have some faulty features. In other words, many Free Fire player express their disappointments because of bugs that occurred in the game. Previous research shows that support team responsiveness related to technical errors are one of the factors that may affect player drop out on games (Lebres et al., 2018). These bugs can vary from graphical glitches that affect the visual quality of the game to more critical issues like crashes or game balance problems (Tufano et al., 2022).

The complexity of modern video games, with their vast worlds and intricate mechanics, makes manual bug detection increasingly challenging (Wilkins et al., 2020). Garena may need to look for the most important bugs that affects user's experience first. Visual bugs, such as graphical glitches that occur during GUI rendering, are common in graphically-rich applications like video games and can significantly impact the overall quality of the game (Chen et al., 2021). Detecting these visual bugs requires specialized approaches that combine visual and textual information to identify and understand issues reported by users effectively (Cooper et al., 2021). By leveraging techniques like deep reinforcement learning and anomaly detection, developers can augment automated testing processes to detect and address visual bugs more efficiently (Bergdahl et al., 2020; Wilkins et al., 2020).

As for the second topic, it mostly talks about graphics and performance issues. It's shown by word '*patah'* or stutter. Beside performance, in this topic, players also complain about the graphics of the game. One word, which is included in the list of profanity words also contain such complaint related to graphic. According to Lebres et al., performance issues are one of the factors on why player quit playing a game. erformance issues encompass a range of factors, including latency, rendering processes, memory allocation, graphical components, and real-time processing, all of which can affect the game's responsiveness and visual quality (Agrahari & Chimalakonda, 2020). These issues can lead to gameplay disruptions, such as lag, frame rate drops, stuttering, and overall sluggishness, detracting from the immersive experience that players expect (Agrahari & Chimalakonda, 2020). These further shows that those aspects of the game need to be improved although the effort may be huge.

Upon analysis, the third topic appears to represent the comments of individuals who have been suspended for engaging in illegal top-up activities, potentially without their knowledge of the illegality of such actions. Consequently, they have decided to retire ("pensi") from playing the game Free Fire. A lot of players express that their account got suspended or banned without strong reason behind it. Terms like 'suspend' prove this point. Technologies like real-time detection systems have been developed to identify and intervene in cases of harassment or rule-breaking during gameplay, enabling companies to issue warnings, mute players, or impose bans as necessary (Stoop et al., 2019). However, the effectiveness of such measures in influencing player behavior and ensuring compliance remains a

subject of ongoing evaluation (Xiao, 2023). Garena must evaluate the administrative action done related to player's account, whether this is a valid complaint or the opposite, it needs to be further investigated. In summary, the result of topics interpretation can be seen on Figure 4

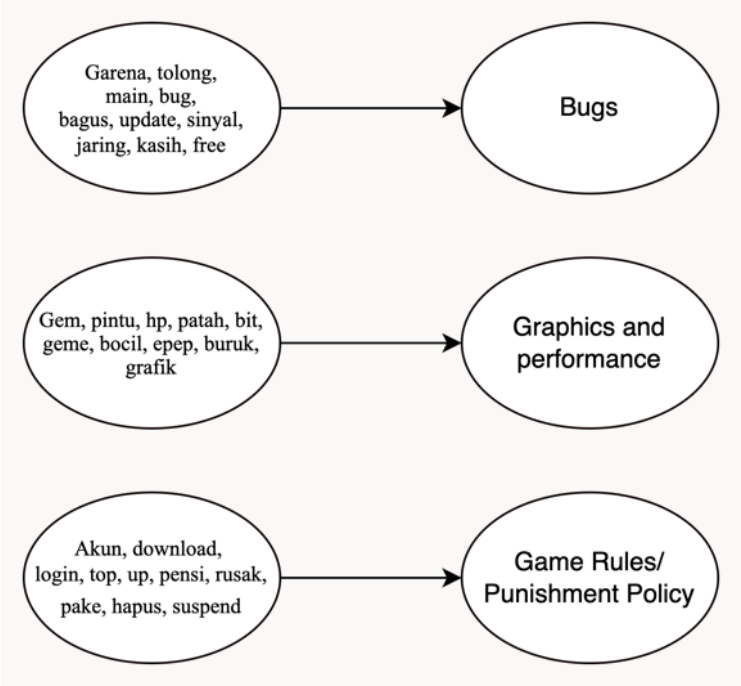

Figure 4. Topic Interpretation

Conclusion

This research on topic modeling using Google Play reviews and Latent Dirichlet Allocation (LDA) has gained a result of which aspects of the Free Fire game are users mostly concerned with. The three main topics that were generated from this research includes bugs, graphic and performance and game rules/punishment policy. The model generated from this research have a coherence score comparable to previous research and therefore considered to be quite interpretable.

The next step of this research is to further dive into each topic. Starting from bugs issue, Garena may need to strengthen their quality assurance process and find out what are the most common problems found by players. Next, in terms of performance, although the effort required to improve game performance is quite big, opinions from users show that it has quite an influence on player's experience. Garena need to make sure their games adapt well to lower-end devices, as many users has expressed their dissatisfaction toward in-game performance. Finally, related to punishment policy, Garena may have to conduct evaluation on their administrative action towards player's account to decide whether the current set of processes has accurately achieved its goal of preventing players misbehaving against the game rules.

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References

Aaputra, S. A., Didi Rosiyadi, Windu Gata, & Syepry Maulana Husain. (2019). Sentiment Analysis Analysis of E-Wallet Sentiments on Google Play Using the Naive Bayes Algorithm Based on Particle Swarm Optimization. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *3*(3).

Abdel-Karim, B. M., Pfeuffer, N., Rohde, G., & Hinz, O. (2020). How and What Can Humans Learn from Being in the Loop? *KI - Künstliche Intelligenz*, *34*(2).

Agrahari, V., & Chimalakonda, S. (2020). A Catalogue of Game-Specific Anti-Patterns. *CoRR*, *abs/2006.13129*.

Amarasinghe, K., Manic, M., & Hruska, R. (2015). Optimal stop word selection for text mining in critical infrastructure domain. *Proceedings - 2015 Resilience Week, RSW 2015*.

Bergdahl, J., Gordillo, C., Tollmar, K., & Gisslen, L. (2020). Augmenting Automated Game Testing with Deep Reinforcement Learning. *IEEE Conference on Computatonal Intelligence and Games, CIG*, *2020-August*.

Cai, Y., & Sun, J.-T. (2009). Text Mining. In *Encyclopedia of Database Systems* (pp. 3061–3065). Springer US.

Chen, H., Xie, L., Leung, C. C., Lu, X., Ma, B., & Li, H. (2017). Modeling latent topics and temporal distance for story segmentation of broadcast news. *IEEE/ACM Transactions on Audio Speech and Language Processing*, *25*(1).

Chen, K., Li, Y., Chen, Y., Fan, C., Hu, Z., & Yang, W. (2021). GLIB: Towards automated test oracle for graphically-rich applications. *ESEC/FSE 2021 - Proceedings of the 29th ACM Joint Meeting European Software Engineering Conference and Symposium on the Foundations of Software Engineering*.

Cooper, N., Bernal-Cardenas, C., Chaparro, O., Moran, K., & Poshyvanyk, D. (2021). It takes two to tango: Combining visual and textual information for detecting duplicate video-based bug reports. *Proceedings - International Conference on Software Engineering*.

Drus, Z., & Khalid, H. (2022). It Takes Three to Tango: Understanding the World of Online Gossips through Netnography, Big Data Topic Modelling and Sentiment Analysis. *2022 IEEE/ACIS 7th International Conference on Big Data, Cloud Computing, and Data Science (BCD)*, 166–171.

Fuad, A., Bayoumi, S., & Al-Yahya, H. (2020). A recommender system for mobile applications of google play store. *International Journal of Advanced Computer Science and Applications*, *11*(9).

Goyal, A., & Kashyap, I. (2022). Latent dirichlet allocation - an approach for topic discovery. *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)*.

Gustafson, N., Pera, M. S., & Ng, Y. K. (2008). Nowhere to hide: Finding plagiarized documents based on sentence similarity. *Proceedings - 2008 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2008*.

Hermanto, Kuntoro, A. Y., Asra, T., Pratama, E. B., Effendi, L., & Ocanitra, R. (2020). Gojek and Grab User Sentiment Analysis on Google Play Using Naive Bayes Algorithm and Support Vector Machine Based Smote Technique. *Journal of Physics: Conference Series*, *1641*(1).

Hossain, M. S., & Rahman, M. F. (2024). Detection of readers' emotional aspects and thumbs-up empathy reactions towards reviews of online travel agency apps. *Journal of Hospitality and Tourism Insights*, *7*(1).

Kim, M., & Lee, S. M. (2023). Unpacking the Drivers of Dissatisfaction and Satisfaction in a Fitness Mobile Application. *Behavioral Sciences*, *13*(9).

Kim, S. W., & Gil, J. M. (2019). Research paper classification systems based on TF-IDF and LDA schemes. *Human-Centric Computing and Information Sciences*, *9*.

Kwak, M., Park, J. S., & Shon, J. G. (2020). Identifying critical topics for successful games in game reviews by applying latent Dirichlet allocation. *Lecture Notes in Electrical Engineering*, 41–48.

Lebres, I., Rita, P., Moro, S., & Ramos, P. (2018). Factors determining player drop-out in Massive Multiplayer Online Games. *Entertainment Computing*, *26*.

Lee, D. G., & Seo, Y. S. (2020). Improving bug report triage performance using artificial intelligence based document generation model. *Human-Centric Computing and Information Sciences*, *10*.

Li, X., Ouyang, J., Zhou, X., Lu, Y., & Liu, Y. (2015). Supervised labeled latent dirichlet allocation for document categorization. *Applied Intelligence*, *42*(3).

Li, X., Zhang, Z., & Stefanidis, K. (2021). A data-driven approach for video game playability analysis based on players' reviews. *Information (Switzerland)*, *12*(3).

Lin, D., Bezemer, C. P., Zou, Y., & Hassan, A. E. (2019). An empirical study of game reviews on the Steam platform. *Empirical Software Engineering*, *24*(1).

Maryamah, M., Arifin, A. Z., Sarno, R., & Sholikah, R. W. (2019). Enhanced topic modelling using dictionary for questions and answers problem. *Proceedings of 2019 International Conference on Information and Communication Technology and Systems, ICTS 2019*.

Nawang Sari, W. A., & Dwi Purnomo, H. (2022). Topic Modeling Using the Latent Dirichlet Allocation Method on Wikipedia Pandemic COVID-19 Data in Indonesia. *Jurnal Teknik Informatika (Jutif)*, *3*(5), 1223–1230.

Negara, E. S, Triadi, D., & Andryani, R. (2019). Topic Modelling Twitter Data with Latent Dirichlet Allocation Method. *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)*, 386–390.

Rao, A. V. S. S. R., & Ranjana, P. (2020). Empower good governance with public assessed schemes by improved sentiment analysis accuracy. *Electronic Government*, *16*(1–2).

Sea Limited. (2021). *Form 20-F, Sea Annual Report 2021*. https://cdn.sea.com/webmain/static/resource/seagroup/pressrelease/2021AR/9OnCqBAnsNMu6SWhHzoP/2022-04-22%20-%20Form%20-F.pdf

Sharma, C. R. (2019). *Sea ltd: New game pipeline, crystallizing ecommerce valuation - and other feedback from investors*. https://www.proquest.com/reports/sea-ltd/docview/2251053237/se-2

Stoop, W., Kunneman, F., van den Bosch, A., & Miller, B. (2019). Detecting harassment in real-time as conversations develop. *Proceedings of the Third Workshop on Abusive Language Online*.

Tan, X. (2020). Topic extraction and classification method based on comment sets. *Journal of Information Processing Systems*, *16*(2), 329–342.

Tufano, R., Scalabrino, S., Pascarella, L., Aghajani, E., Oliveto, R., & Bavota, G. (2022). Using Reinforcement Learning for Load Testing of Video Games. *Proceedings - International Conference on Software Engineering*, *2022-May*.

Vukanti, V., & Jose, A. (2021). Business Analytics: A case-study approach using LDA topic modelling. *5th International Conference on Computing Methodologies and Communication (ICCMC)*, 1818–1823.

Wilkins, B., Watkins, C., & Stathis, K. (2020). A Metric Learning Approach to Anomaly Detection in Video Games. *IEEE Conference on Computatonal Intelligence and Games, CIG*, *2020-August*.

Xiao, L. Y. (2023). Breaking Ban: Belgium's Ineffective Gambling Law Regulation of Video Game Loot Boxes. *Collabra: Psychology*, *9*(1).

Yoshida, T., Hisano, R., & Ohnishi, T. (2023). Gaussian hierarchical latent Dirichlet allocation: Bringing polysemy back. *PLoS ONE*, *18*(7 JULY).

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