STUDENT ADOPTION OF BUSINESS INTELLIGENCE (BI) TOOLS: COMPARING MICROSOFT POWER BI AND GOOGLE LOOKER STUDIO USING UTAUT

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ABSTRACT

Objective: This study explores the adoption of Microsoft Power BI and Google Looker Studio in Business Intelligence (BI) learning using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to determine which BI tool demonstrates higher acceptance, usability, and perceived effectiveness among polytechnic students.

Research Method: A quantitative research design was employed involving 78 students from Semesters 4 and 5 of the Information and Communications Technology Department (JTMK), Politeknik Sultan Idris Shah (PSIS). Data were analysed through descriptive statistics to measure students' perceptions across UTAUT constructs.

Findings: The results showed that both tools achieved moderate-to-high to high levels of acceptance, with Performance Expectancy being the strongest construct for both platforms. However, Google Looker Studio outperformed Microsoft Power BI, particularly in effort expectancy, social influence, and facilitating conditions, owing to its ease of use, collaborative functionality, and seamless integration within the Google ecosystem. These advantages fostered more positive student attitudes and stronger behavioural intentions toward continued use. Conversely, Power BI was valued for its analytical strengths but was perceived as more complex and required greater instructional support.

Originality: This study offers empirical evidence comparing two principal BI tools within Technical and Vocational Education and Training (TVET) contexts. Findings suggest Looker Studio is appropriate for introductory BI courses, whereas Power BI is essential for advanced analytical skills.

Keywords: Business Intelligence (BI) Tools, Microsoft Power BI, Google Looker Studio, Student Perception, UTAUT Framework

1. INTRODUCTION

Business Intelligence (BI) has become a vital component of modern education, equipping students with analytical skills to transform raw data into actionable insights. As organisations increasingly adopt data-driven decision-making, Higher Education Institutions (HEIs) have begun integrating BI tools into their curricula to enhance students' data literacy and practical competencies. Among the wide range of available BI platforms, Microsoft Power BI and Google Looker Studio are two of the most widely adopted due to their accessibility, visualisation capabilities, and industry relevance. Both platforms share the fundamental purpose of converting data into insightful dashboards, yet they differ significantly in terms of usability, functionality, and learning experience. Power BI, supported by Microsoft's ecosystem, offers advanced analytics and enterprise-level scalability. Conversely, Looker Studio emphasises ease of use, real-time collaboration, and integration with Google's cloud-based services. This makes it especially appealing to students who value simplicity and accessibility.

Although the use of BI tools is growing, most studies have focused on corporate or higher education environments, leaving limited evidence on the pedagogical application within the polytechnic and TVET context for BI learning. TVET institutions prioritise the development of students' technical and vocational skills to meet workforce demands and are increasingly adopting learning analytics and data analytics to improve teaching and learning (Othman et al., 2023). However, the complexity of certain BI platforms may hinder engagement and confidence, particularly among novice learners. Power BI is widely recognised as a powerful analytic tool but is often perceived as technically demanding due to its advanced modelling features and the usage of DAX expression language for new columns and calculations. Studies mention that mastering DAX and understanding complex data models in Power BI are considered present significant learning challenges (Skender, 2022) and many modelling features may further confuse beginners (Addepalli et al., 2023).

In contrast, Looker Studio offers free online tool and a web-based environment with an intuitive drag-and-drop interface that enables effortless dashboard creation (Aksoy et al., 2025; Fishelson et al., 2023) It provides a simple, low-cost, practical visualisation system and supports seamless collaboration through unrestricted sharing and real-time report editing (Hassan et al., 2024). Despite these contrasting features, empirical research comparing students' experiences with different BI tools, particularly in TVET settings remains scarce where understanding such differences is crucial for selecting tools that best foster engagement and practical learning outcomes.

Therefore, this study aims to explore the adoption of Microsoft Power BI and Google Looker Studio in BI learning, focusing on polytechnic student experiences through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The analysis compares student perceptions of usefulness, ease of use, engagement, social influence, facilitating conditions, attitude toward use, and behavioural intention between both tools. By examining these dimensions, the study provides valuable insights for educators seeking to optimise BI teaching strategies and make informed tool selections. The rest of this paper is structured as follows: Section 2 reviews existing literature regarding BI in education and the application of the UTAUT framework. Section 3 outlines the research methodology, and Section 4 shows the results and discusses the findings. Finally, Section 5 concludes the study and proposes directions for future research.

2. LITERATURE REVIEW

This literature review examines three key dimensions relevant to the present study: the role and significance of BI in education, the strengths and limitations of Microsoft Power BI and Google Looker Studio and the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework in understanding technology adoption among students. Together, these perspectives provide the foundation for analysing students' acceptance and experiences with BI tools in higher education.

2.1 BUSINESS INTELLIGENCE IN AN EDUCATIONAL CONTEXT

As educational data gets more complicated and the need for evidence-based decision-making grows, HEIs need better ways to analyse data. Business Intelligence (BI), also called Business Analytics (BA), is a broad category of technologies, applications, systems, tools, tactics, processes, and strategies used to collect, combine, store, access, analyse, and share data (Abduldaem & Gravell, 2021; Hmoud et al., 2023). It involves transforming raw and extensive datasets into valuable knowledge or actionable insights. The adoption of BI in HEIs shows measurable gains, enhancing decision-making, improving operational efficiency, and increasing student success and academic performance (Alkhwaldi et al., 2025).

Moreover, the rapid application of BI across diverse educational contexts, from higher HEIs (Sequeira et al., 2024) to Technical and Vocational Education and Training (TVET) institutions (Mohamed Isa et al., 2024), accentuates its essential role. This widespread implementation serves dual purposes: institutions use BI platforms to visualise institutional performance (Abduldaem & Gravell, 2021) and identify at-risk students (Othman et al., 2023), and BI tools serve a pedagogical purpose in BI education, essentially cultivating students' analytical thinking, data literacy, and problem-solving skills (Alkhwaldi et al., 2025). Students are increasingly expected to analyse data and derive meaningful insights independently using tools such as Microsoft Power BI and Google Looker Studio for data visualisation, which support interactive learning through dynamic dashboards, data modelling, and real-time reporting features (Mohamed Isa et al., 2024; Gurcan et al., 2023; Shi et al., 2024; Sequeira et al., 2024). Consequently, BI has become a necessity for modern, data-driven HEIs seeking to remain competitive and efficient. In polytechnic settings that emphasise applied learning and industry readiness, students focus on practical competencies, making ease of use and institutional support critical to BI tool adoption.

2.2 THE STRENGTHS AND LIMITATIONS OF MICROSOFT POWER BI AND GOOGLE LOOKER STUDIO

Microsoft Power BI and Google Looker Studio represent two widely adopted BI platforms, each with distinct characteristics designed to meet different organisational and analytical needs. Power BI is highly regarded for its enterprise-level capabilities, particularly its ability to work with large datasets and a wide range of data sources, including files, databases, cloud services like Azure, and online services such as GitHub and social media platforms (Miteva & Stefanova, 2022; Mohamed Isa et al., 2024). It has robust data transformation capabilities through Power Query and advanced analytical functions through Data Analysis Expressions (DAX), both of which are integrated into the larger Microsoft ecosystem (Banerjee et al., 2024; Kadam & Akhade, 2024; Das et al., 2023). Additionally, the platform is adaptable to different user contexts due to its availability across desktop, web, and mobile versions (Skender & Manevska, 2022). However, Power BI presents certain limitations. The platform has a steep learning curve, especially for users unfamiliar with DAX and Power Query functions (Skender & Manevska, 2022). Additionally, constraints on customisation and the complexity of its interface can pose barriers for novice users (Kadam & Akhade, 2024; Addepalli et al., 2023).

Google Looker Studio excels in terms of usability, accessibility and collaboration through its fully web-based design (Addepalli et al., 2023; Borra, 2024). It facilitates the creation of visualisation with minimal technical knowledge, making it highly suitable for educational environments (Pemungkas & Sapruddin, 2025; Egan & Mohamed Akbar, 2025). Its intuitive drag-and-drop interface, a wide range of visualisation options, seamless integration with all Google Cloud Applications, and work well with various data sources such as Google Analytics, BigQuery, and Google Sheets enhance its practicality and ease of use (Addepalli et al., 2023; Borra, 2024). Furthermore, it offers powerful capabilities that enable the effective communication of complex information through data visualisation (Vibhute et al., 2023). Its collaborative features and low learning curve make it ideal for providing data access in educational settings and smaller teams (Hassan et al., 2024; Patel, 2023). Nonetheless, its simplicity that makes Looker Studio so appealing also belies its drawbacks, which include a lack of real-time analytics, advanced modelling, and comprehensive data processing capabilities (Addepalli et al., 2023). However, empirical research remains limited, particularly within polytechnic education, where understanding how usability and accessibility influence student tool preference is still underexplored.

2.3 UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT) FRAMEWORK

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework, proposed by Venkatesh et al. (2003) represents a comprehensive approach to understanding technology adoption by systematically integrating eight existing models, including the Theory of Reasoned Action (TRA) and Technology Acceptance Model (TAM) to explain and predict technology acceptance and behavioural intention. At its core, UTAUT identifies four primary constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). PE, EE, and SI were theorised and found to directly influence Behavioural Intention (BI) or Intention to Use (ITU), while BI and FC determined Use Behaviour (UB/UBE) (Venkatesh et al., 2003; Venkatesh et al., 2016). The framework's theoretical strength is matched by its exceptional empirical performance, demonstrating 70% explanatory power for behavioural intentions (Venkatesh et al., 2003) and proven superiority over all previous models.

The original UTAUT framework excluded Attitude (ATU/ATT/AT/ATUT) when PE and EE were present (Venkatesh et al., 2003). However, Dwivedi et al. (2019) through meta-UTAUT, stated that ATU was central to BI and UB, it partially mediated the effects of UTAUT constructs on BI, and it had a direct influence on actual UB. Figure 1 illustrates this revised conceptual model, showing ATU as a mediating variable linking the antecedents (PE, EE, SI, and FC) to BI and subsequently to UB. Later studies, such as by Chatterjee et al. (2021) further validated the mediating role of ATU in connecting these antecedents to BI and UB. Similarly, Handayani, (2023) examined the behavioural intention of mobile banking users and confirmed that ATU positively mediated the relationship between PE and BI, considering that ATU is the biggest predictor of BI. Furthermore, research on Unified Payments Interface (UPI) adoption showed that the model effectively predicts ATU and UB. PE strongly influenced ATU, while ATU, SI, and FC significantly affected BI (Rahim et al., 2024).

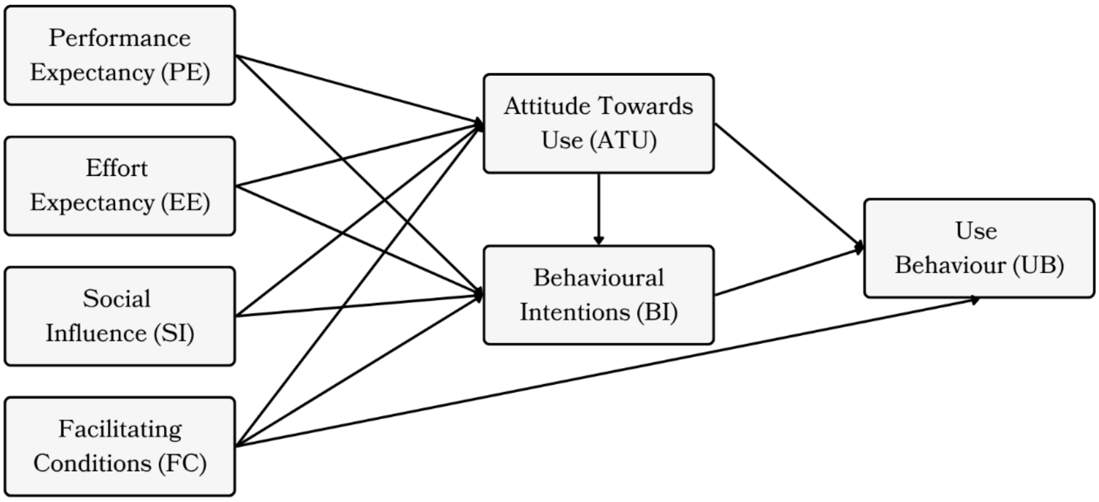

Figure 1: Revised UTAUT Model Incorporating Attitude Towards Use
Source: (Dwivedi et al., 2019)

This necessity for refinement spurred later extensions, including a modified UTAUT by Al-Sayid & Kirkil (2024) that integrates TAM and extended meta-UTAUT models by Rahim et al. (2024) incorporating Trust and Personal Innovativeness, all demonstrating the framework's adaptability to evolving technological and contextual requirements.

2.4 APPLICATION OF UTAUT TECHNOLOGY ADOPTION IN EDUCATION

The UTAUT remains one of the most robust frameworks for examining technology adoption across educational contexts, with a major focus on HEIs. Recent research is largely centred on predicting student acceptance of rapidly advancing technologies like Artificial Intelligence (AI), continuance intention for e-learning systems and social media. Empirical research affirms that the advantages of technology are a primary driver for its adoption in HEIs. For instance, studies by Xu et al. (2025) focusing on generative AI acceptance by college students found that PE exerted the greatest positive influence on BI, followed by EE, SI, and FC, with BI and FC remaining strong determinants of actual UB. This finding is consistent across investigations of AI-based academic support among students in Malaysian and Pakistani HEIs (Ahmed Dahri et al., 2024). However, the predictive strength of these constructs varies significantly by the specific application context. For instance, a study on academic advising chatbots in UAE HEIs found that EE and SI were significant factors, while PE was not (Bilquise et al., 2023).

Beyond AI, the traditional UTAUT constructs proved effective for predicting student acceptance of online learning technology in HEIs, where all four predictors significantly influenced BI and UB (Arifin et al., 2025). In studies focusing on e-learning system continuance intentions in Turkish universities, FC often emerged as a key determinant of BI, demonstrating the model's high explanatory power, sometimes accounting for over 70% of the variance in intentions (Al-Sayid & Kirkil, 2025). In terms of polytechnic contexts, a study by Awang Siman et al. (2025) on the perception of polytechnic students adopting social media for interactive learning found that SI was the strongest predictor of their ITU, with PE and EE also playing significant roles. Overall, the results reinforce that while PE remains a dominant factor in new technology adoption, the importance of EE, SI, and FC shifts significantly based on the system's nature, user experience, and mandatory environment. While UTAUT is well established in HEIs, research on its use in polytechnic and TVET contexts, especially for BI tool adoption, has remained limited.

To address this gap, the present study employs a quantitative approach to compare polytechnic students' adoption of Power BI and Looker Studio using the UTAUT framework. The following section details the research design, participant characteristics, and data collection procedures.

3. METHODOLOGY

This section covers the research design, participants, instruments, and procedures employed to examine students' adoption of Business Intelligence (BI) tools, Microsoft Power BI and Google Looker Studio, within the UTAUT framework.

3.1 RESEARCH DESIGN AND PARTICIPANTS

This study used a quantitative survey design involving students from Semesters 4 and 5 of the Diploma in Information Technology (DIT) programme under the Department of Information and Communications Technology (JTMK), Politeknik Sultan Idris Shah (PSIS). A purposive sampling technique was employed, whereby all students who were enrolled in the DFP40162 Business Intelligence course as part of their diploma programme were selected as participants. This sampling approach was appropriate because all enrolled students had completed hands-on learning activities with Microsoft Power BI and Google Looker Studio within a structured learning environment, ensuring they possessed direct experience with both tools to provide informed perceptions for the study.

Prior to data collection, Power BI and Looker Studio were introduced through identical lesson structures during class sessions involving hands-on demonstration, guided practice and supplementary learning materials such as dashboard design layout guides and best practice examples were shared to enhance students' understanding of effective BI dashboard design and development. Following the instructional sessions, students were assigned a group project-based task consisting of three or four persons per group that required them to: (1) connect to provided datasets, (2) perform data cleaning and transformation, (3) create a minimum of four interactive reports, (4) design a cohesive dashboard layout following best practices, and (5) publish the dashboard for online access using both BI tools. This process ensured that all participants had adequate exposure and balanced exposure to both tools before completing the survey. The research activities flow is shown in Figure 2.

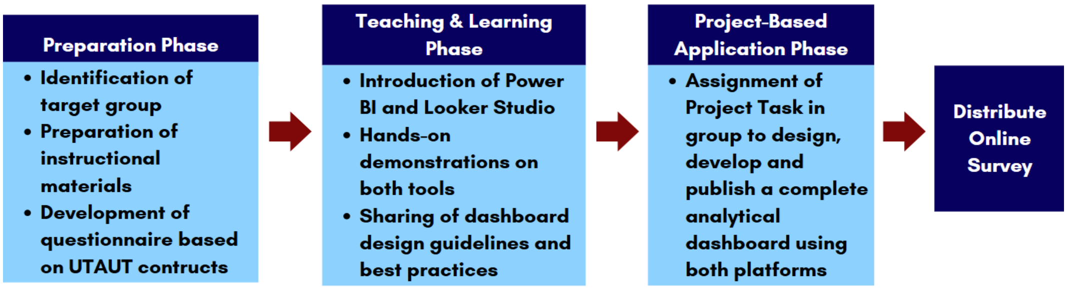

Figure 2: Research Activity Flow

3.2 INSTRUMENT DEVELOPMENT, DATA COLLECTION AND DATA ANALYSIS PROCEDURES

This study employs six constructs from the UTAUT framework to examine both the direct determinants of technology acceptance—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—as well as the mediating construct Attitude Toward Use (ATU) and the outcome variable Behavioral Intention (BI). The inclusion of ATU and BI enables a comprehensive assessment of how these antecedent factors influence students' emotional acceptance and their motivation to continue using BI learning tools. Performance Expectancy (PE), defined as the extent to which students believe the BI tool improves their learning performance, has been shown to be a dominant predictor of BI in studies on Generative AI and other educational technologies (Xu et al., 2025; Chatterjee et al., 2021).

Effort Expectancy (EE), referring to perceived ease of use, is also widely validated as a significant contributor to system adoption, particularly in e-learning settings (Al-Sayid & Kirkil, 2024). Social Influence (SI) captures the degree to which students feel encouraged by peers or educators to use the BI tool, and has demonstrated strong positive effects in TVET contexts (Awang Siman et al., 2025). Facilitating Conditions (FC), which relate to institutional and technical support, have similarly been confirmed as important predictors of adoption (Al-Sayid & Kirkil, 2024). Attitude Toward Use (ATU) reflects students' affective responses toward the BI tool and operates as a central mediating factor in meta-UTAUT models, shaping emotional acceptance (Chatterjee et al., 2021; Handayani, 2023). Finally, Behavioral Intention (BI) represents students' motivation or likelihood of continued use and is widely recognised as the strongest antecedent of actual technology usage (Rahim et al., 2024). Together, these six constructs provide a robust framework for understanding acceptance and sustained engagement in BI learning environments.

These constructs collectively guided the design of the survey instrument used in this study. The survey instrument used a structured questionnaire consisting of 36 items, with 18 items for each BI tool developed based on the UTAUT framework, adapted from validated instruments employed in previous technology adoption studies (Venkatesh et al., 2003; Attuquayefio & Addo, 2014; Handayani, 2023) and contextualised to align with the Business Intelligence learning environment within polytechnic settings. Reliability analysis via Cronbach's Alpha demonstrated excellent internal consistency for the overall instrument ($\alpha = 0.95$) and satisfactory reliability for each construct: Performance Expectancy ($\alpha = 0.81$), Effort Expectancy ($\alpha = 0.78$), Social Influence ($\alpha = 0.72$), Facilitating Conditions ($\alpha = 0.81$), Attitude Toward Use ($\alpha = 0.73$), and Behavioural Intention ($\alpha = 0.70$). All values exceeded the recommended reliability threshold of $\alpha \geq 0.70$ (Ahmad et al., 2024), confirming the instrument's high reliability and suitability for subsequent analysis.

The survey instrument is divided into four sections, namely Sections A, B, C, and D. Section A gathered demographic information; Section B measured factors that influence students' acceptance of BI tools in terms of PE and EE of Microsoft Power BI and Google Looker Studio; Section C evaluated SI and FC for both tools; and Section D measured students' resulting attitudes and intentions after being influenced by the factors through ATU and BI. The survey was administered at the end of the BI module using Google Forms to facilitate efficient data collection.

A 4-point Likert scale was utilised, ranging from "Strongly Disagree (1)" to "Strongly Agree (4)". The absence of a neutral midpoint encouraged respondents to provide a clear stance, promoting decisive feedback (Brown, 2000; Krosnick & Presser, 2010). The study adopted the classification method proposed by Alico & Guimba (2015) to interpret the mean scores, which divides mean values into four levels: Low (1.00–1.74), Moderate-Low (1.75–2.49), Moderate-High (2.50–3.24), and High (3.25–4.00). This categorisation enabled consistent interpretation of students' perception levels across all UTAUT constructs. Data were analysed using SPSS software. Descriptive statistics were employed to summarise demographic profiles and evaluate students' perceptions of both BI tools across UTAUT constructs.

4. RESULTS AND DISCUSSIONS

Based on this methodology, the following sections present the demographic characteristics of participants, conduct a comparative analysis of student perceptions regarding Microsoft Power BI and Google Looker Studio across UTAUT constructs, and interpret these findings in relation to BI learning in polytechnic education.

4.1 DEMOGRAPHIC ANALYSIS OF RESPONDENTS

The study included 78 students in semesters 4 and 5 from the JTMK, PSIS who were enrolled in the DFP40162 Business Intelligence course. Most respondents were in Semester 4, accounting for 97.44% (n=76), with only 2.56% (n=2) from Semester 5. In terms of gender, 38.46% (n=30) were female and 61.54% (n=48) were male. Regarding prior experience using BI tools, 51.28% (n=40) reported having no prior experience before enrolling in this course, and 48.72% (n=38) had experience using them. Over half of these students, 53.85% (n=42), had used Looker Studio, followed by Power BI at 42.31% (n=33) and other tools at 3.85% (n=3). In terms of computer proficiency, 55.13% (n=43) reported intermediate skills, 41.03% (n=32) beginner, and 3.85% (n=3) advanced. Overall, the findings indicate that most students possess moderate digital competency, providing ideal context to assess perceptions from both novice and experienced learners.

4.2 COMPARATIVE ANALYSIS OF BI TOOLS ADOPTION (UTAUT CONSTRUCTS)

This section presents students' perceptions toward Power BI and Looker Studio in BI learning, which are evaluated through the six (6) UTAUT constructs. The purpose of this analysis is to identify which BI tool demonstrates higher acceptance, usability, and perceived effectiveness among students, as well as to provide insights for educators and curriculum designers in improving teaching strategies, resource allocation, and tool integration in BI-related courses.

4.2.1 PERFORMANCE EXPECTANCY (PE)

Performance Expectancy (PE) measures students' perceptions regarding the efficacy of each BI tool in improving their learning performance.

Table 1: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Performance Expectancy (PE)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Performance Expectancy (PE)	PE1: It helps me better understand business or organisational data.	3.31	0.65	High	3.47	0.60	High

	PE2: The tools and functions available support my learning of BI concepts, especially in creating data visualisation	3.28	0.70	High	3.49	0.64	High
	PE3: I find using this tool helps me perform better in my assessments.	3.24	0.81	Moderate -high	3.40	0.65	High
Overall PE		3.28	0.72	High	3.45	0.63	High

Results in Table 1 indicate that both tools achieved a moderate-high to high level of performance expectancy, with means ranging from 3.24 to 3.49 and standard deviations (S.D.) indicating moderate response consistency (0.60–0.81). For both tools, the highest-rated indicator was PE2, confirming that the tools and functions effectively support learning BI concepts and data visualisation (Power BI: *M* = 3.28, *S.D.* = 0.70; Looker Studio: *M* = 3.49, *S.D.* = 0.64). This was closely followed by PE1, suggesting both enhance understanding of organisational data. The primary difference was in PE3, where Power BI's score (*M* = 3.24, *S.D.* = 0.81) fell to a moderate-high level, while Looker Studio (*M* = 3.40, *S.D.* = 0.65) maintained a high level. Overall, the findings indicate that Looker Studio was perceived as slightly more effective and consistent in enhancing students' learning performance compared to Power BI, as reflected by its higher mean scores across all indicators (*M* = 3.40–3.49) and overall mean score (*M* = 3.45). This suggests that educators and curriculum designers could integrate Looker Studio more extensively in BI courses to leverage its intuitive visualisation and collaborative features to design interactive reports and dashboards, while maintaining Power BI for advanced analytical exercises requiring greater modelling depth.

4.2.2 EFFORT EXPECTANCY (EE)

Effort Expectancy (EE) measures students' perceptions regarding the ease of use, interface clarity, and skill acquisition for each tool.

Table 2: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Effort Expectancy (EE)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Effort Expectancy (EE)	EE1: My interaction is clear and understandable.	3.26	0.76	High	3.38	0.63	High
	EE2: The interface is easy to use and navigate.	3.19	0.88	Moderate -high	3.40	0.69	High
	EE3: It is easy to become skilful using this tool.	3.17	0.83	Moderate -high	3.38	0.63	High
Overall EE		3.21	0.82	Moderate -high	3.39	0.65	High

Results in Table 2 show that both tools obtained moderate-high to high levels of effort expectancy, with mean scores ranging from 3.17 to 3.40 and standard deviations (S.D.) between 0.63 and 0.88, indicating moderate response consistency among students. The highest-rated indicator for both tools was EE1 (Power BI: *M* = 3.26, *S.D.* = 0.76; Looker Studio: *M* = 3.38, *S.D.* = 0.63), suggesting that students found their interactions with both tools clear and understandable. However, for EE2 and EE3, Power BI recorded moderate-high levels (*M* = 3.19, 3.17; *S.D.* = 0.88, 0.83), while Looker Studio maintained high levels (*M* = 3.40, 3.38; *S.D.* = 0.69, 0.63), indicating that students perceived Looker Studio as easier to use, more intuitive, easier to navigate and quicker to master.

Overall, the results suggest that Looker Studio offers a smoother learning curve and higher ease of use, as reflected by its higher mean scores across all indicators (*M* = 3.39-3.40) and overall mean score (*M* = 3.39), while Power BI may require additional guidance or structured tutorials. Hence, educators could provide scaffolded practice sessions or step-by-step exercises for Power BI, while curriculum designers might include comparative learning modules that leverage Looker Studio's simplicity to build foundational confidence before progressing to Power BI's more advanced analytics, urging students to develop proficiency in both tools for comprehensive BI competency.

4.2.3 SOCIAL INFLUENCE (SI)

Social Influence (SI) examines the extent to how much peers, educators, and institutions encourage students to use each BI tool.

Table 3: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Social Influence (SI)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Social Influence (SI)	SI1: My classmates encouraged me to use this tool for BI assessments.	3.00	0.93	Moderate-high	3.31	0.76	High
	SI2: My lecturer recommends that I use this tool to enhance my BI learning.	3.42	0.68	High	3.46	0.64	High
	SI3: In general, my institution has supported the use of this tool for learning Business Intelligence.	3.38	0.67	High	3.45	0.62	High
Overall SI		3.27	0.76	High	3.41	0.67	High

The outcome in Table 3 indicates that both tools achieved moderate-high to high levels of social influence, with mean scores ranging from 3.00 to 3.46 and standard deviations (S.D.) between 0.62 and 0.93, reflecting moderate response consistency among participants. The highest-rated indicator for both tools was SI2 (Power BI: *M* = 3.42, *S.D.* = 0.68; Looker Studio: *M* = 3.46, *S.D.* = 0.64), showing that educator recommendations played a key role in motivating students to use these BI tools for learning. This was followed by SI3 (Power BI: *M* = 3.38, *S.D.* = 0.67; Looker Studio: *M* = 3.45, *S.D.* = 0.62), indicating strong institutional encouragement for tool adoption. In contrast, peer influence (SI1) had the lowest means, with Power BI (*M* = 3.00, *S.D.* = 0.93) at a moderate-high level and Looker Studio (*M* = 3.31, *S.D.* = 0.76) at a high level, suggesting that peer encouragement for Looker Studio was more consistent and widespread.

Overall, Looker Studio demonstrated stronger social support and acceptance, as reflected by its higher mean scores across all indicators (*M* = 3.31-3.45) and overall mean score (*M* = 3.41). This implies that educators should continue reinforcing peer collaboration, peer-led discussion and sharing best practices, while curriculum designers could formalise structured peer learning or group projects to strengthen social influence and collective engagement in BI learning environments across both tools.

4.2.4 FACILITATING CONDITIONS (FC)

Facilitating Conditions assess the availability of resources, knowledge, and technical support for using each BI tool.

Table 4: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Facilitating Condition (FC)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Facilitating Condition (FC)	FC1: I have the necessary resources (labs, internet, tutorials) to use this tool effectively.	3.40	0.65	High	3.42	0.61	High
	FC2: I have the necessary knowledge to use this tool effectively.	3.13	0.84	Moderate -high	3.29	0.61	High
	FC3: I can get help when I encounter problems using this tool.	3.15	0.82	Moderate -high	3.42	0.55	High
Overall FC		3.23	0.77	Moderate -high	3.38	0.59	High

Results in Table 4 show that both tools attained moderate-high to high levels of facilitating conditions, with mean scores ranging from 3.13 to 3.42 and standard deviations (S.D.) between 0.55 and 0.84, indicating a moderate level of consistency among respondents. The highest-rated indicator for both tools was FC1 (Power BI: *M* = 3.40, *S.D.* = 0.65; Looker Studio: *M* = 3.42, *S.D.* = 0.61), suggesting that students felt adequately supported with resources such as labs, internet access, and tutorials to use both tools. For FC2 and FC3, Power BI recorded moderate-high levels (*M* = 3.13, 3.15; *S.D.* = 0.84, 0.82), whereas Looker Studio achieved high levels (*M* = 3.29, 3.42; *S.D.* = 0.61, 0.55), showing that students perceived Looker Studio to have better technical support, accessibility, and guidance when encountering challenges.

Overall, Looker Studio demonstrated stronger facilitating conditions to use the tool, as reflected by its higher mean scores across all indicators (*M* = 3.29-3.42) and overall mean score (*M* = 3.38). This advantage stems from its seamless integration with cloud-based resources and Google's collaborative ecosystem, which collectively enhance students' access to guidance and their ability to resolve issues efficiently.

Hence, educators should prioritise strengthening instructional support for Power BI through structured tutorials, shared learning materials, and guided workshops to address its steeper learning curve. At the same time, curriculum designers should ensure equitable access to technical guidance and learning infrastructure for both tools to enhance students' confidence, independence and self-sufficiency in BI learning.

4.2.5 ATTITUDE TOWARD USE (ATU)

Attitude Toward Use measures students' affective responses based their emotions, such as liking, enjoyment, and interest when using each BI tool.

Table 5: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Attitude Toward Use (ATU)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Attitude Toward Use (ATU)	ATU1: I like working with this tool.	3.10	0.91	Moderate -high	3.38	0.69	High
	ATU2: I enjoy using this tool for creating data visualizations and dashboards.	3.18	0.79	Moderate -high	3.33	0.68	High
	ATU3: I believe using this tool makes learning Business Intelligence more interesting.	3.19	0.79	Moderate -high	3.45	0.57	High
Overall ATU		3.16	0.83	Moderate -high	3.39	0.65	High

The outcome in Table 5 reveals that both tools obtained moderate-high to high levels of attitude toward use, with mean scores ranging from 3.10 to 3.45 and standard deviations (S.D.) between 0.57 and 0.91, suggesting moderate consistency in students' responses. For Power BI, all three indicators were rated at a moderate-high level (*M* = 3.10, 3.18, 3.19; *S.D.* = 0.91, 0.79, 0.79), showing that while students generally liked and enjoyed using the tool, their enthusiasm was moderate. In contrast, Looker Studio achieved high levels across all items (*M* = 3.38, 3.33, 3.45, *S.D.* = 0.69, 0.68, 0.57), indicating stronger positive attitudes, enjoyment, and interest in using the tool for creating data visualisations and dashboards. The highest-rated indicator for both tools was ATU3 (Power BI: *M* = 3.19, *S.D.* = 0.79; Looker Studio: *M* = 3.45, *S.D.* = 0.57), suggesting that students found BI learning more engaging using these platforms.

Overall, Looker Studio was perceived by students as a more enjoyable and favourable tool, as reflected by its higher mean scores across all indicators (*M* = 3.33-3.45) and overall mean score (*M* = 3.39). This positive perception reflects its user-friendly design, intuitive interface, lower learning curve and smoother user experience. To strengthen students' attitudes toward Power BI, educators should develop more engaging and helpful learning experiences, including gamified exercises, analytics projects based on real-world data, or peer-led demonstrations, to make the tool's complex features more approachable and rewarding to use. Meanwhile, curriculum designers could integrate both tools in a complementary sequence, using Looker Studio to foster confidence and enjoyment in BI visualisation before advancing to Power BI for deeper analytical and modelling practices in BI learning.

4.2.6 BEHAVIOURAL INTENTION (BI)

Behavioural intention measures how willing students are to keep using, investigate advanced features, and suggest each BI tool to their peers.

Table 6: Comparison of Microsoft Power BI and Google Looker Studio in Terms of Behavioural Intention (BI)

Construct	Indicator	Microsoft Power BI			Google Looker Studio		
		Mean	S.D.	Level	Mean	S.D.	Level
Behavioural Intention (BI)	BI1: I plan to use this tool after this course.	3.03	0.95	Moderate-high	3.28	0.79	High
	BI2: I want to explore more of its advanced features.	3.24	0.81	Moderate-high	3.36	0.68	High
	BI3: I would recommend it to other students.	3.18	0.88	Moderate-high	3.40	0.74	High
Overall BI		3.15	0.88	Moderate-high	3.35	0.74	High

Results in Table 6 indicate that both tools achieved moderate-high to high levels of behavioural intention, with mean scores ranging from 3.03 to 3.40 and standard deviations (S.D.) between 0.68 and 0.95, reflecting moderate variability among students' responses. For Power BI, all three indicators were rated at a moderate-high level (*M* = 3.0, 3.24, 3.18; *S.D.* = 0.95, 0.81, 0.88), suggesting that students were somewhat willing to keep using the tool, but they weren't very committed to it in the long term. In contrast, Looker Studio obtained high levels across all indicators (*M* = 3.28, 3.36, 3.40; *S.D.* = 0.79, 0.95, 0.74), indicating a stronger intention among students to keep using, exploring, and recommending the tool beyond the course. The highest-rated item for both tools was BI3 (Power BI: *M* = 3.18, *S.D.* = 0.88; Looker Studio: *M* = 3.40, *S.D.* = 0.74), showing that students were most inclined to recommend Looker Studio to their peers.

Overall, these findings highlight that Looker Studio fosters stronger behavioural intentions for continued use and user loyalty, as reflected by its higher mean scores across all indicators (*M* = 3.28-3.40) and overall mean score (*M* = 3.35). This is advantageous due to its accessibility, collaborative features, and integration with familiar Google applications. Therefore, educators should focus on reinforcing students' long-term engagement with Power BI by integrating real-world projects or certification-linked tasks that highlight its professional relevance and practical value. Meanwhile, curriculum designers could leverage students' stronger intentions toward Looker Studio to make it a gateway tool for creative visualisation and collaborative learning and then move on to Power BI for advanced analytical tasks. This complementary approach can sustain students' motivation while deepening their proficiency and long-term adoption of both BI tools.

4.3 OVERALL CONSTRUCTS COMPARISONS

This section summarises the overall mean scores of all six (6) UTAUT constructs for Microsoft Power BI and Google Looker Studio. The constructs were then ranked from the highest to lowest mean to identify which dimensions most strongly influenced students' perceptions of each tool. The results are presented in Table 7.

Table 7: Summary of Mean Scores and Rankings Across All UTAUT Constructs

Construct	Microsoft Power BI		Google Looker Studio	
	Mean	Rank	Mean	Rank
Performance Expectancy (PE)	3.28	1	3.45	1
Social Influence (SI)	3.27	2	3.41	2
Effort Expectancy (EE)	3.21	4	3.39	3
Facilitating Conditions (FC)	3.23	3	3.38	5
Attitude Toward Use (ATU)	3.16	5	3.39	3 (tie)
Behavioural Intention (BI)	3.15	6	3.35	6

Both tools ranked highest for PE (Power BI: M = 3.28; Looker Studio: M = 3.45), signifying those students perceived them as effective for enhancing their analytical and learning performance. SI ranked second for both tools (Power BI: M = 3.27, Rank 2; Looker Studio: M = 3.41, Rank 2), indicating that peers, educators and institutional endorsements played a significant role in shaping students' perceptions.

In general, Looker Studio did better than Power BI on all six UTAUT constructs, with overall mean scores ranging from 3.35 to 3.45 (high level) compared to Power BI's overall mean scores ranging from 3.15 to 3.28 (moderate-high and high level). The biggest differences between the tools were observed in three key areas: ATU (0.23), where Looker Studio made students feel better about using it; EE revealed a notable difference (0.18), indicating that Looker Studio was perceived as significantly easier to use; and FC demonstrated a meaningful disparity (0.15), where students thought technical support and knowledge were easier to find in Looker Studio. Notably, while BI was the lowest for both products, Looker Studio showed a better commitment to continuing use than Power BI.

4.4 DISCUSSIONS

The overall results reveal that both Microsoft Power BI and Google Looker Studio achieved moderate-high to high acceptance levels across all UTAUT constructs, showing positive students' perceptions towards BI tools in the learning environment. However, Looker Studio consistently surpassed Power BI, especially in EE, SI and FC. It had higher mean scores and more consistent responses. These findings suggest that Looker Studio provides a more effective, user-friendly, and supportive learning experience for BI education. Students in the advanced, intermediate, and beginner groups consistently rated Google Looker Studio higher than Microsoft Power BI for all UTAUT constructs, indicating that competency level did not change the overall acceptance for Looker Studio. In contrast, Power BI was recognised for its advanced analytical power but required additional instructional support to facilitate learning and engagement because it was thought difficult to understand.

In the present study, PE ranked highest for both tools, whereas BI recorded the lowest mean values. Students perceived that the BI tool enhanced their learning performance and data analytics understanding but were not enthusiastic to continue using it. This gap is more prevalent in Power BI compared to Looker Studio, where mean BI was categorised as moderate-high (M = 3.15). In contrast, Looker Studio achieved higher ratings for both PE and BI (PE: M = 3.45; BI: M = 3.35), indicating a high level of continued adoption intention. This disparity highlights a common pattern observed in UTAUT-based studies, where a strong perception of utility does not necessarily translate into continued use unless ease of use or emotional engagement is sufficient (Venkatesh et al., 2003; Chatterjee et al., 2021). Previous studies in educational contexts similarly report that long-term technology adoption depends not only on performance gains but also on supportive factors such as EE, ATU, and SI (Handayani, 2023; Awang Siman et al., 2025; Xu et al., 2025).

The disconnect between strong PE and low BI can be explained through the mediating effects of EE and ATU. The meta-UTAUT model highlights ATU as a central construct linking antecedent factors such as PE and EE to adoption intention

(Chatterjee et al., 2021; Handayani, 2023). Tools that are easy to use and enjoyable effectively convert high PE into sustained adoption (Chatterjee et al., 2021). Power BI's moderate-high EE (*M* = 3.21) and ATU (*M* = 3.16) acted as barriers between perceived performance and adoption intention. Although Power BI is acknowledged as a powerful and robust enterprise analytics platform (Das et al., 2023; Skender & Manevska, 2022), some sources indicate it requires steeper learning demands, particularly for users who are new to the platform (Patel, 2023). Students may appreciate what Power BI can do, but if they perceive it as more complex (low EE) and the experience is not enjoyable (low ATU), then the motivation to continue using it diminishes. These effects are consistent with e-learning findings showing that EE strongly predicts system adoption (Al-Sayid & Kirkil, 2025).

Conversely, Looker Studio's superior ease of use (EE: *M* = 3.39) and positive emotional engagement (ATU: *M* = 3.39) show how simplicity and enjoyment reinforce learning. With its intuitive drag-and-drop interface, a wide range of visualisation options, seamless integration with all Google Cloud Applications, collaborative features, and low learning curve, Looker Studio is ideal for providing data access in educational settings and smaller teams (Hassan et al., 2024; Borra, 2024; Patel, 2023; Addepalli et al., 2023). Studies affirm that the use of effective and intuitive BI tools enhances data-driven understanding and improving decision-making processes (Hurbean et al., 2025; Khadam & Akhade, 2024; Addepalli et al., 2023). Therefore, within polytechnic learning environments, the perceived ease of use and positive emotional engagement of a tool may be as critical as its analytical capability.

SI emerged as a significant determinant of BI. Both tools received high overall SI mean scores (Power BI, *M* = 3.27*;* Looker Studio, *M* = 3.41). While both tools gained strong institutional and educator endorsement, there is a significant gap in peer influence (SI1: Looker Studio *M* = 3.31; Power BI *M* = 3.00). This reveals that while institutional and educator support is necessary, it is insufficient without strong peer endorsement for adoption intention. In the context of polytechnic students, peer influence serves as a catalyst for technology acceptance. This aligns with prior studies highlighting that interactive visualisation platforms enhance engagement and foster social learning dynamics (Hassan et al., 2024; Miteva & Stefanova, 2022). In addition, Looker Studio's seamless sharing and real-time collaboration features (Hassan et al., 2024) contribute to higher peer influence compared to Power BI's more individualised workflow (Al-Sayid & Kirkil, 2024). These collaborative features are in line with UTAUT claims that SI affects both ATU and BI through social interaction and collaborative settings (Handayani, 2023; Chatterjee et al., 2021; Miteva & Stefanova, 2022). Consequently, BI learning environments that encourage peer collaboration and shared learning, like Looker Studio, will cultivate stronger motivation and sustained intention to use.

FC further strengthened Looker Studio's advantage, with higher mean scores (*M* = 3.38) indicating that students found it easier to access guidance, technical resources, and troubleshooting support. Its fully web-based and cloud-integrated design (Kahn, 2023) enables seamless support and troubleshooting while allowing users to collaborate and share reports easily through links (Kahn, 2023; Hassan et al., 2024; Boyaci, 2025). In contrast, Power BI's desktop-based setup and licensing requirements limited immediate access, requiring structured tutorials and workshops to build students' confidence and self-sufficiency (Skender, 2022). These findings correspond with the UTAUT theory, which states that strong FC directly enhances usage behaviour by reducing technical barriers and ensuring sufficient institutional and technical infrastructure (Venkatesh et al., 2012). Similar patterns have been identified in e-learning and TVET contexts, where strong institutional support, financial resources, and user-friendly cloud-based systems are critical drivers of learning technology adoption and sustained student engagement in higher education (Mukred et al., 2024; Al-Sayid & Kirkil, 2025; Chatterjee et al., 2021; Awang Siman et al., 2025).

The positive learning experience associated with Looker Studio directly correlated with higher BI scores. It indicates a cohesive emotional and behavioural acceptance pattern. Students not only enjoyed using Looker Studio but were also more inclined to continue using and recommending it (BI3: Looker Studio M = 3.40; Power BI M = 3.18). These findings align with prior research demonstrating that positive attitudes driven by perceived enjoyment and ease of use strengthen students' satisfaction and motivation for sustained adoption. (Al-Sayid & Kirkil, 2025; Handayani, 2023; Chatterjee et al., 2021). In TVET and polytechnic contexts, technologies that reduce cognitive effort and foster interactive engagement strengthen learning motivation and promote long-term adoption. Hence, educators should consider balancing technical capability with user experience design when introducing BI tools to novice learners.

5. CONCLUSIONS

This study evaluated the adoption of Microsoft Power BI and Google Looker Studio in business intelligence learning among polytechnic students through the UTAUT framework, comparing six constructs: PE, EE, SI, FC, ATU, and BI. Empirical results indicate both tools were well-received, with moderate-high to high ratings for all constructs, reflecting strong acceptance and relevance in BI education. Nevertheless, Looker Studio demonstrated superior performance compared to Power BI, evidenced by consistently higher mean scores (ranging from 3.35 to 3.45) and reduced variance in student responses, indicating a more uniform and positive perception among students.

Students perceived Looker Studio as more effective in enhancing learning performance, easier to use, better supported technically, and more engaging for continued use. Key differences emerged in EE, SI, and FC, where Looker Studio outperformed Power BI. These differences were due to Looker Studio's easy-to-use interface, built-in collaboration tools, and smooth integration with the existing Google ecosystem. On the other hand, Power BI offers robust analytical features, its complexity highlights the importance of guided instruction to ensure effective student adoption.

These findings suggest that educators should strategically use both tools to complement each other's strengths. Looker Studio for basic BI concepts and group projects that focus on motivating learners and increasing their learning interest, and Power BI for more advanced analytics and business-level skills. Curriculum designers should ensure balanced instructional support through scaffolded tutorials, peer-learning activities, and hands-on projects to enhance social interaction and sustained engagement across both platforms.

This study has several limitations. The single-institution sample, predominantly comprising Semester 4 students (97.44%), limits the generalisability of findings across different educational settings and student demographics. Moreover, as most polytechnics currently rely on Power BI while few incorporate Looker Studio, the comparative scope remains narrow. Additionally, the cross-sectional design captures only students' initial perceptions rather than long-term skill retention or sustained tool usage patterns.

Future research should expand the study by including applying predictive modelling using machine learning and multi-institutional and longitudinal samples to examine BI tool adoption over time. Objective measures of learning performance and qualitative approaches, such as focus groups or interviews, could further illuminate how students select and apply BI tools in different analytical contexts. Exploring differences by discipline, academic level, and prior technical experience would also provide deeper insights into BI adoption behaviours and learning effectiveness.

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