FACTORS AFFECTING BLENDED LEARNING ACCEPTANCE BASED ON UTAUT2 AND TPACK MODELS AMONG EDUCATORS AT A PUBLIC EDUCATION INSTITUTION IN MALAYSIA

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Abstrak

Pembelajaran Teradun (Blended Learning, BL) semakin diberi penekanan dalam pendidikan tinggi Malaysia selaras dengan agenda transformasi digital nasional. Walaupun sokongan dasar dan pembangunan infrastruktur telah diperkukuh, tahap penerimaan dan penggunaan BL dalam kalangan staf akademik masih tidak konsisten. Keadaan ini menunjukkan bahawa faktor penerimaan teknologi sahaja mungkin tidak mencukupi untuk menjelaskan kesediaan pendidik menggunapakai BL, terutamanya apabila keupayaan pengetahuan pengajaran turut memainkan peranan penting. Kajian ini mengintegrasikan model Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) dan kerangka Technological Pedagogical Content Knowledge (TPACK) bagi menganalisis hubungan struktural antara faktor penerimaan teknologi dan kesiapsiagaan pengetahuan pengajaran dalam meramalkan niat tingkah laku serta penggunaan sebenar BL dalam kalangan pendidik. Menggunakan kaedah pensampelan berstrata, data dikumpulkan daripada 300 orang staf akademik merentas fakulti dan pusat akademik di sebuah universiti awam di Malaysia. Saiz sampel ini dianggap mencukupi bagi memastikan kuasa statistik yang memadai untuk analisis pemodelan persamaan berstruktur. Data dianalisis menggunakan Partial Least Squares Structural Equation Modelling (PLS-SEM) bagi menilai kebolehpercayaan pengukuran, kesahan konstruk serta hubungan struktural. Dapatan menunjukkan bahawa Jangkaan Prestasi, Jangkaan Usaha, Pengaruh Sosial, Keadaan Kemudahan, Motivasi Hedonik, Tabiat serta komponen Pengetahuan Pedagogi, Pengetahuan Kandungan dan Pengetahuan Teknologi mempengaruhi Niat Tingkah Laku secara signifikan seterusnya meramalkan Penggunaan Sebenar BL. Keadaan Kemudahan dikenal pasti sebagai peramal paling dominan, sekali gus menegaskan kepentingan sokongan institusi dan infrastruktur. Analisis moderasi turut menunjukkan bahawa umur dan pengalaman mengajar memoderasi hubungan antara Pengetahuan Teknologi dan Niat Tingkah Laku. Kajian ini mengesahkan kesesuaian model bersepadu UTAUT2–TPACK dalam menjelaskan penerimaan BL dalam konteks institusi pengajian tinggi awam di Malaysia. Dapatan kajian memperkukuh literatur sedia ada dengan menunjukkan pengaruh gabungan antara penerimaan teknologi dan pengetahuan pengajaran, di samping menekankan keperluan latihan profesional yang bersasar serta sokongan institusi yang berterusan bagi memastikan pelaksanaan BL yang berkesan dan mampan.

Kata kunci: Pembelajaran Teradun; UTAUT2; TPACK; Institusi Pengajian Tinggi; PLS-SEM

Abstract

Blended Learning (BL) is increasingly emphasised in Malaysian higher education in line with national digital transformation policies. Despite institutional support and infrastructure development, the adoption and sustained use of BL among academic staff remain inconsistent. This suggests that technology acceptance factors alone may not sufficiently explain educators' readiness to adopt BL, particularly when instructional knowledge capabilities are equally critical. This study integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Technological Pedagogical Content Knowledge (TPACK) framework to analyse the structural relationships between technology acceptance factors and instructional knowledge readiness in predicting educators' behavioural intention and actual use of BL. Using a stratified sampling approach, data were collected from 300 academic staff across faculties and academic centres at a Malaysian public university. The sample size was considered sufficient to ensure adequate statistical power for structural equation modelling. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate measurement reliability, construct validity, and structural relationships. The findings indicate that Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Habit, and the TPACK components of Pedagogical Knowledge, Content Knowledge, and Technological Knowledge significantly influenced Behavioural Intention, which subsequently predicts the Actual Use of BL. Facilitating Conditions demonstrated the strongest direct effect, underscoring the importance of institutional and infrastructural support. Moderation analysis further revealed that age and teaching experience significantly moderated the relationship between Technological Knowledge and Behavioural Intention. This study validates an integrated UTAUT2–TPACK model in explaining BL adoption within a Malaysian public higher education institution. The findings strengthen the existing literature by demonstrating the combined influence of technology acceptance and instructional knowledge, while highlighting the need for targeted professional development and sustained institutional support to ensure effective and sustainable BL implementation.

Keywords: Blended Learning; UTAUT2; TPACK; Higher Education Institution; PLS-SEM

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"Work; so Allah will see your work and (so will) His Messenger and the believers."

(Quran, At-Tawbah 9:105)

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List of Abbreviations

AU	Actual Use
BI	Behavioural Intention
BL	Blended Learning
CAD	Centre for Academic Development
CK	Content Knowledge
EE	Effort Expectancy
FC	Facilitating Conditions
GLOBAL	Centre for Global Online Learning
HEIs	Higher Education Institutions
HM	Hedonic Motivation
HT	Habit
ICT	Information and Communication Technology
KPI	Key Performance Indicator
PE	Performance Expectancy
PK	Pedagogical Knowledge
PLS	Partial Least Squares
SEM	Structural Equation Modelling
SI	Social Influence
SPSS	Statistical Package for the Social Sciences
TK	Technological Knowledge
TPACK	Technological Pedagogical Content Knowledge
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
UTHM	Universiti Tun Hussein Onn Malaysia
VIF	Variance Inflation Factor

CHAPTER ONE
INTRODUCTION

1.0 Introduction

This chapter introduces the study by focusing on the adoption of Blended Learning (BL) within Malaysian Higher Education Institutions (HEIs). It outlines the emergence of BL as a technology-enabled learning arrangement that integrates face-to-face instruction with online learning environments, highlighting the associated challenges encountered in its implementation within contemporary higher education settings. Central to this chapter is the identification of factors that influence the adoption and use of BL in the Malaysian HEI context.

The chapter begins by presenting the contextual background of the study, underscoring the increasing relevance of BL in the digital transformation of higher education in Malaysia. It addresses the growing demand for learning environments that combine physical and digital modes of delivery to support flexible access to learning resources and institutional digitalisation efforts. In the context of this study, the online component of BL comprises both synchronous and asynchronous modes. Synchronous learning refers to real-time online interactions such as virtual lectures and live discussions, while asynchronous learning involves self-paced activities, including recorded lectures, learning management system (LMS) materials, and online assessments. The integration of these online modes with face-to-face instruction reflects current BL practices adopted by Malaysian HEIs.

The chapter then outlines the problem statement, which highlights the limited understanding of the factors influencing academic staff adoption and sustained use of

BL. This leads to the formulation of the research questions and research objectives, which define the scope and direction of the study.

A description of the research framework is subsequently presented to establish the theoretical grounding of the study. The framework integrates two established models: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Technological Pedagogical Content Knowledge (TPACK) framework. Based on these theoretical foundations, research hypotheses are developed to guide the empirical investigation.

The delimitations of the study are then specified to clarify the scope and boundaries of the research, including contextual and methodological considerations that may influence the interpretation of the findings. This is followed by a discussion of the significance of the study, outlining its potential contributions to research on the adoption of BL and technology integration in higher education. Finally, key terms and study variables are defined and operationalised to ensure conceptual clarity and consistency throughout the thesis.

1.1 Background of the Study

The Fourth Industrial Revolution (Industry 4.0), introduced in 2011 in Germany, has fundamentally reshaped industries and everyday life through the integration of advanced digital technologies (Lasi et al., 2014). Across successive industrial revolutions, organisations have been required to continuously adapt to technological, social, and regulatory changes to remain relevant and effective (Brown & Harvey, 2006; Drath & Horch, 2014). Within the education sector, these transformations have contributed to the emergence of Education 4.0, which emphasises the purposeful integration of digital technologies into teaching and learning processes. This paradigm shift has heightened expectations for higher education graduates to demonstrate not only disciplinary knowledge but also the ability to function effectively in technology-mediated environments, thereby prompting higher education institutions (HEIs) to re-examine traditional face-to-face instructional practices and incorporate online learning components.

Since gaining independence in 1957, Malaysia has made significant progress in expanding educational access and strengthening its higher education system (Malaysia Education Blueprint 2013–2025, 2013). Guided by the Ministry of Education and the Ministry of Higher Education, national policies have increasingly prioritised the integration of educational technologies as part of broader digitalisation efforts. These initiatives include strong emphasis on Science, Technology, Engineering, and Mathematics (STEM), Technical and Vocational Education and Training (TVET), and the systematic use of Information and Communication Technologies (ICTs). Within Malaysian HEIs, learning management systems (LMS), digital platforms, and technology-mediated instructional approaches have become integral to teaching and learning delivery, enabling the combination of conventional face-to-face instruction with online learning activities.

The COVID-19 pandemic, which began in late 2019, further accelerated the adoption of technology-mediated learning and underscored the crucial role of ICT in ensuring the continuity of higher education provision (Dhawan, 2020). During this period, BL, commonly defined as the structured integration of face-to-face instruction with online learning environments (Garrison & Kanuka, 2004; Graham, 2006), was widely implemented across HEIs. In practice, BL in Malaysian universities involves a combination of physical classroom interaction and online learning delivered through both synchronous and asynchronous modes. Synchronous online learning typically included real-time virtual lectures, discussions, and consultations conducted via video-conferencing platforms, while asynchronous learning encompassed pre-recorded lectures, discussion forums, digital learning materials, and self-paced activities hosted on LMS platforms.

Prior studies indicate that well-designed BL environments can enhance access to learning resources, support flexibility, and promote learner engagement when compared to fully traditional face-to-face instruction (Debra & Bourke, 2010; Garrison & Vaughan, 2008). However, the rapid and large-scale shift towards online and blended modalities during the pandemic also exposed significant challenges related to technological access, institutional preparedness, and academic staff capability in managing both synchronous and asynchronous learning activities effectively. These challenges were particularly evident when face-to-face pedagogical practices were transferred directly into online environments without sufficient adaptation to the affordances and constraints of digital platforms.

In the Malaysian context, national policy documents such as the Malaysia Education Blueprint 2015–2025 (Higher Education) have formally positioned blended and flexible learning as strategic priorities for enhancing access and supporting digital transformation within HEIs. In response, many universities have institutionalised BL as part of their instructional delivery systems. At Universiti Tun Hussein Onn Malaysia (UTHM), for instance, the introduction of the Full Online Classroom (FOC) initiative in 2017 marked a significant step towards integrating online learning components alongside face-to-face instruction, with expanded implementation during and after the pandemic period. These initiatives reflect institutional efforts to align with national digitalisation agendas while increasing reliance on academic staff to design, manage, and deliver instruction across physical classrooms and online environments.

Despite the widespread institutionalisation of BL in Malaysian higher education, empirical evidence suggests that its adoption and sustained use among academic staff remain uneven and inconsistent (Chung et al., 2020; Yahaya & Mohd Jawi, 2020; Yusoff et al., 2021). Existing studies within Malaysian HEIs have largely focused on institutional readiness, student perceptions, or technology use during emergency remote teaching, with limited emphasis on academic staff's behavioural intention to adopt BL as a deliberate instructional approach that integrates face-to-face teaching with synchronous and asynchronous online learning (Dhawan, 2020; Bond et al., 2021).

Furthermore, prior research has frequently examined technology acceptance factors or pedagogical knowledge in isolation, without adequately capturing the combined influence of acceptance-related determinants and the professional knowledge of academic staff required to manage technology-mediated instruction effectively (Chai et al., 2013; Scherer et al., 2019). As a result, there remains a lack of empirically validated models that explain how technology acceptance and knowledge readiness jointly shape academic staff's intention to adopt and use BL in a post-pandemic higher education context, particularly within Malaysian public universities.

1.2 Problem Statement

Against this background, as Malaysia aligns its tertiary education system with global digital advancements, the integration of ICTs, particularly through BL, has become a strategic priority. BL, which combines face-to-face instruction with online learning, has been associated with enhanced student engagement, interaction, flexibility, and access to learning resources (Garrison & Kanuka, 2004; Dickfos et al., 2014; Manwaring et al., 2017). Consequently, BL is increasingly positioned not merely as an alternative instructional approach but as an expected mode of delivery within higher education institutions (HEIs).

In response, Malaysian HEIs have implemented national and institutional initiatives to support BL adoption. Under the Malaysia Education Blueprint 2015–2025 (Higher Education), the Ministry of Higher Education introduced the Full Online Classroom (FOC) initiative in 2017, setting a national target of at least 50% BL implementation across public universities (Ministry of Education Malaysia, 2015). These initiatives reflect a strong policy-level commitment to digital transformation and technology integration in higher education.

Despite these strategic efforts and relatively well-developed ICT infrastructure, the integration and sustained use of BL among academic staff remain uneven. Within the Malaysian Technical University Network (MTUN), universities have invested substantially in digital platforms, learning management systems (LMS), and professional development to support technology-enabled teaching. At Universiti Tun Hussein Onn Malaysia (UTHM), BL initiatives have been actively implemented through dedicated units such as the Centre for Global Online Learning (GLOBAL), including the development of MOOCs and the institutionalisation of FOC.

Nevertheless, these efforts highlight an ongoing challenge in translating infrastructural readiness and policy expectations into consistent instructional practices among academic staff.

Evidence from internal institutional briefings and administrative monitoring indicates that participation in instructional technology training remains below optimal levels, with BL implementation rates declining in recent years and falling short of institutional key performance indicators. Although these data are derived from internal monitoring rather than publicly archived reports, they point to persistent challenges in sustaining BL practices. This situation suggests that access to technology alone is insufficient, highlighting the need to examine academic staff's acceptance of educational technologies and their knowledge of how to integrate them meaningfully into teaching practices.

To examine these challenges, established theoretical frameworks offer valuable analytical perspectives. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) explains behavioural intention and actual technology use, while the Technological Pedagogical Content Knowledge (TPACK) framework conceptualises the knowledge domains required for effective technology integration. However, prior studies have predominantly examined these frameworks independently, resulting in limited understanding of how acceptance-related factors and professional knowledge jointly influence BL adoption (Chan et al., 2022; Anthony et al., 2024; Vo et al., 2024).

Furthermore, although demographic variables such as age, gender, and teaching experience are widely examined as moderators within technology acceptance research, their influence on academic staff's technological, pedagogical, and content knowledge has received comparatively less empirical attention. Existing studies tend to focus on the structure of TPACK rather than variations in knowledge readiness across academic staff profiles (Chai et al., 2013; Koehler et al., 2013). Accordingly, this study applies demographic moderators specifically to the TPACK knowledge components rather than re-examining moderation effects within UTAUT2.

While this study is situated at UTHM, it is framed within the broader context of Malaysian public higher education institutions. By integrating UTAUT2 and TPACK and applying demographic moderators to the knowledge components, this study aims to generate contextually grounded insights into academic staff's technology acceptance and knowledge readiness for BL. The findings are expected to inform institutional strategies and national policy initiatives aimed at supporting the sustainable integration of BL in Malaysian higher education.

1.3 Research Objectives

The research objectives outlined in this study are designed to comprehensively investigate the adoption and utilisation of BL as a teaching method among academic staff at UTHM. These objectives are crafted to shed light on the multifaceted dynamics that influence academic staff's behavioural intentions to adopt BL and how these intentions translate into actual use. The study aims to provide valuable insights into the challenges and opportunities faced by UTHM academic staff in integrating BL into their teaching practices, employing a combination of theoretical frameworks, including UTAUT2 and TPACK, along with demographic variables. Hence, the primary objectives of this research are as follows:

1. To examine the influence of UTAUT2 variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit) on academic staff's behavioural intention to adopt and use BL as a teaching method in UTHM.

2. To examine the influence of TPACK variables (pedagogical knowledge, content knowledge, and technological knowledge) on academic staff's behavioural intention to accept and use BL as a teaching method in UTHM.

3. To investigate the moderating effects of gender, age, and teaching experience on the relationship between TPACK knowledge components (pedagogical knowledge, technological knowledge, and content knowledge) and academic staff's behavioural intention to accept and use BL as a teaching method in UTHM.

4. To examine the influence of academic staff's behavioural intention on their actual use of BL as a teaching method in UTHM.

These objectives collectively form the backbone of this research endeavour, aiming to provide a comprehensive understanding of the factors influencing the adoption and use of BL among UTHM academic staff.

1.4 Research Questions

The following research questions and sub-questions are designed to explore and understand the relationships among the combination of UTAUT2 and TPACK constructs and academic staff's behavioural intention to adopt and use BL as a teaching method in UTHM.

1.4.1 Research Question 1:

To what extent do UTAUT2 variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit) influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

1.4.1.0 Research Sub-questions:

RQ1. To what extent does performance expectancy influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ2. To what extent does effort expectancy influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ3. To what extent does social influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ4. To what extent do facilitating conditions influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ5. To what extent does hedonic motivation influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ6. To what extent does habit influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

1.4.2 Research Question 2:

To what extent do knowledge variables (pedagogical knowledge, content knowledge, and technological knowledge) influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

1.4.2.0 Research Sub-questions:

RQ2a. To what extent does pedagogical knowledge influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ2b. To what extent does content knowledge influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

RQ2c. To what extent does technological knowledge influence academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

1.4.3 Research Question 3:

Do the demographic variables (gender, age, and teaching experience) moderate the relationship between the TPACK model factors (pedagogical, technological, and content knowledge) and academic staff's behavioural intention to accept and use BL as a teaching method in UTHM?

1.4.4 Research Question 4:

Does academic staff's behavioural intention to accept BL influence their actual use of BL as a teaching method in UTHM?

1.5 Research Framework

This study is guided by an integrated theoretical framework derived from two established models: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Technological Pedagogical Content Knowledge (TPACK) framework. These models collectively constitute the theoretical foundation of the study and provide complementary perspectives for examining academic staff adoption of BL.

UTAUT2 serves as the primary theoretical foundation for explaining academic staff's behavioural intention and actual use of BL through key technology acceptance constructs. The TPACK framework complements UTAUT2 by conceptualising the technological, pedagogical, and content knowledge domains required for academic staff to engage effectively with BL systems. In this study, TPACK is operationalised as a knowledge readiness framework, focusing on pedagogical knowledge (PK), content knowledge (CK), and technological knowledge (TK), rather than on pedagogical practices.

By integrating UTAUT2 and TPACK, the theoretical framework of this study captures both acceptance-driven and knowledge-based dimensions of BL adoption. This integration enables a more comprehensive explanation of how behavioural intention and academic staff knowledge readiness jointly influence the adoption and actual use of BL in a higher education context.

Figure 1.1 presents the conceptual representation of the theoretical framework, illustrating the relationships between UTAUT2 constructs, TPACK-based knowledge components, and actual use of BL. Demographic variables are incorporated as moderators of the TPACK knowledge components to examine variations in academic staff knowledge readiness.

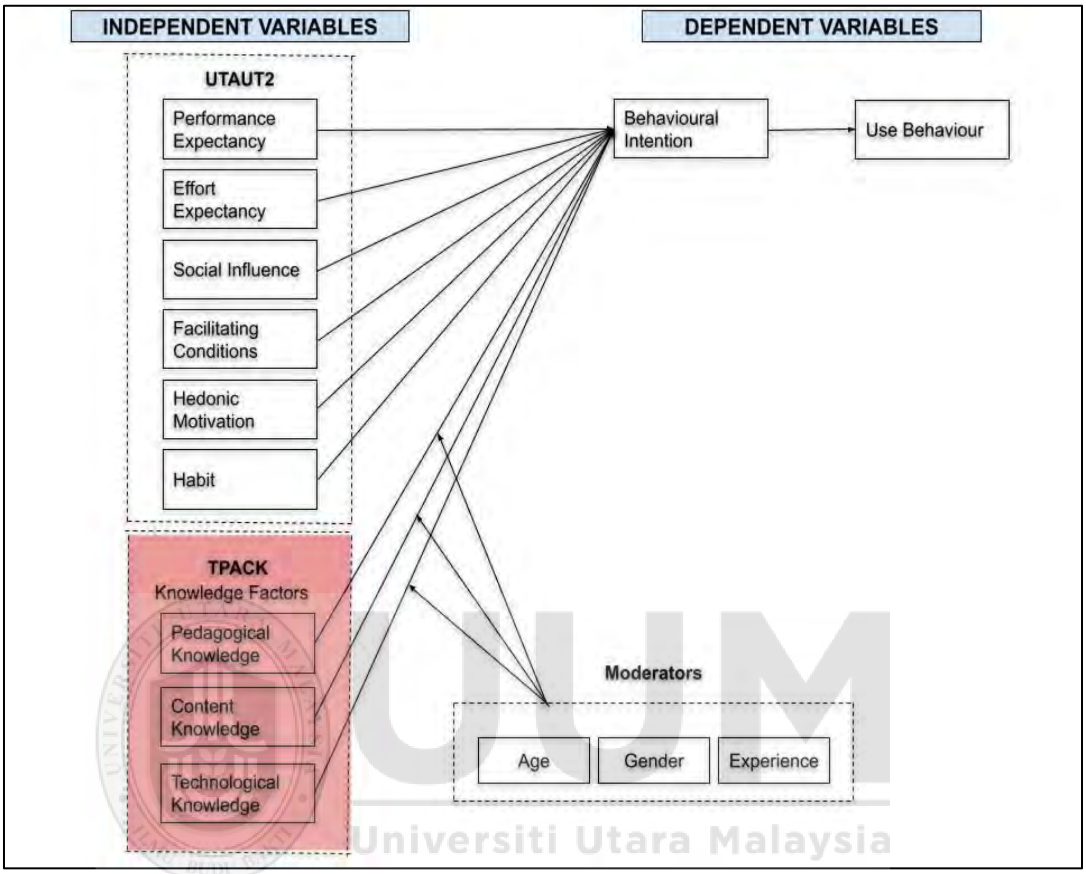

Figure 1.1 Conceptual Framework

The conceptual framework presents the integrated research model that combines UTAUT2 constructs with TPACK knowledge components. The framework illustrates how technology acceptance variables and knowledge-related factors are positioned to examine academic staff's behavioural intention and use of BL. Serving as an analytical structure, this framework guides the investigation of BL adoption among academic staff at UTHM by clarifying the relationships examined in the study.

1.6 Research Hypotheses

The conceptual framework (Figure 1.1) is primarily grounded in the models of Venkatesh et al. (2012) and Mishra and Koehler (2006). Each hypothesis is carefully crafted to directly address the study's objectives. The first set of hypotheses (H1 to H6) is intricately linked with the first research objective, while the second set (H7 to H9) pertains to the second objective. Subsequently, the remaining sub-hypotheses (H11a–H11i) are designed to scrutinise the moderating effects, aligning with the third research objective. H10 is formulated to achieve the fourth research objective, establishing the relationship between Behavioural Intention (BI) and Use Behaviour (USE).

The independent variables encompass Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). This study posits that the relationships between the determinants of Behavioural Intention are subject to moderation by gender, age, and teaching experience, as proposed by Venkatesh et al. (2012). The research hypotheses are structured as follows:

1.6.1 Main Hypotheses

H1: Performance Expectancy (PE) positively influences Behavioural Intention (BI).

H2: Effort Expectancy (EE) positively influences Behavioural Intention (BI).

H3: Social Influence (SI) positively influences Behavioural Intention (BI).

H4: Facilitating Conditions (FC) positively influence Behavioural Intention (BI).

H5: Hedonic Motivation (HM) positively influences Behavioural Intention (BI).

H6: Habit (HT) positively influences Behavioural Intention (BI).

H7: Pedagogical Knowledge (PK) positively influences Behavioural Intention (BI).

H8: Content Knowledge (CK) positively influences Behavioural Intention (BI).

H9: Technological Knowledge (TK) positively influences Behavioural Intention (BI).

H10: Behavioural Intention (BI) positively influences Use Behaviour (USE).

1.6.2 Hypotheses for Moderating Variables

H11a: Gender moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

H11b: Gender moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

H11c: Gender moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

H11d: Age moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

H11e: Age moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

H11f: Age moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

H11g: Teaching Experience moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

H11h: Teaching Experience moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

H11i: Teaching Experience moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

1.7 Delimitations of the Study

This study focuses on examining the acceptance and utilisation of BL among academic staff at UTHM, Parit Raja campus. The investigation centres on identifying factors influencing BL adoption through the integration of the UTAUT2 and TPACK frameworks. The study is delimited to academic staff across various faculties who were involved in undergraduate and postgraduate teaching activities.

Data are collected using an online questionnaire-based survey. The scope of the study is restricted to academic staff at the Parit Raja campus and does not include staff from other UTHM campuses or external institutions. In this study, BL is defined as the combination of face-to-face instruction and online learning environments.

The research is further delimited to the perspectives of academic staff and does not incorporate student views or experiences. In addition, data collection is conducted within a specific time frame, which may not capture longer-term changes or developments in BL adoption practices.

While the findings provide contextually relevant insights into academic staff acceptance and knowledge readiness for BL, the generalisability of the results is limited to higher education institutions with comparable institutional characteristics and technological contexts. Accordingly, the findings should be interpreted within the boundaries of the study's institutional and geographic setting.

1.8 Significance of the Study

This study contributes to the existing body of research by integrating two established theoretical frameworks, UTAUT2 and TPACK, within a single research model to examine the adoption of BL in higher education. By combining UTAUT2's focus on technology acceptance with TPACK's emphasis on academic staff's technological, pedagogical, and content knowledge, the study provides a structured approach for examining both acceptance-related and knowledge-related factors influencing BL adoption. This integration addresses a gap in the literature, where technology acceptance and knowledge-based frameworks have often been examined separately.

From a methodological perspective, the study develops and validates a questionnaire that incorporates constructs from both UTAUT2 and TPACK. This instrument offers a systematic means of capturing technology acceptance and knowledge readiness within a single measurement framework, supporting more comprehensive empirical analysis in studies of BL adoption. As such, the instrument may serve as a reference for future research examining the integration of technology in higher education contexts.

Within the Malaysian higher education setting, the study provides contextually grounded insights into academic staff acceptance and knowledge readiness for BL.

Given the limited number of local studies adopting an integrated acceptance–knowledge approach, the findings offer empirical evidence that may inform institutional decision-making related to professional development, training provision, and technology implementation strategies.

More broadly, the integrated research framework contributes to ongoing discussions on technology integration in higher education by illustrating how acceptance and knowledge dimensions can be examined together within an institutional context. While the findings are specific to BL adoption, the framework may be adapted in future research to explore academic staff engagement with other forms of educational technology, subject to appropriate contextual considerations.

1.9 Operational Definitions for the Study Variables

1.9.1 Adoption

In this study, adoption refers to the acceptance and use of BL by academic staff as part of their teaching activities at UTHM.

1.9.2 Behavioural Intention

Behavioural Intention (BI) refers to an individual's intention or willingness to perform a specific behaviour, such as using or continuing to use a technology (Venkatesh et al., 2003). In this study, BI represents academic staff's intention to adopt and use BL at UTHM.

1.9.3 Blended Learning

BL refers to the integration of face-to-face instruction with online learning environments (Osguthorpe & Graham, 2003). In this study, BL refers to the integration of both physical classroom interaction and ICT-supported online components within the academic staff's teaching activities at UTHM.

1.9.4 Content Knowledge

Content Knowledge (CK) refers to academic staff's understanding of subject matter, including concepts, theories, and disciplinary knowledge relevant to their teaching fields (Mishra & Koehler, 2006). In this study, CK represents academic staff's self-perceived knowledge of their teaching content at UTHM.

1.9.5 Effort Expectancy

Effort Expectancy (EE) refers to the degree of ease associated with the use of a system or technology (Venkatesh et al., 2003). In this study, EE reflects academic staff's perceptions of the effort required to adopt and use BL at UTHM.

1.9.6 Facilitating Conditions

Facilitating Conditions (FC) refer to an individual's perception of the availability of organisational and technical infrastructure to support system use (Venkatesh et al., 2003). In this study, FC represents the academic staff's perceptions of institutional support, technical resources, and infrastructure that facilitate the adoption of BL at UTHM.

1.9.7 Factor

In this study, a factor refers to a theoretical construct derived from the UTAUT2 or TPACK frameworks that is hypothesised to influence academic staff behavioural intention or use of BL within the institutional context of UTHM.

1.9.8 Habit

Habit (HT) refers to the extent to which behaviour is performed automatically as a result of prior experience and repeated use (Limayem, Hirt, & Cheung, 2007). In this study, HT refers to the tendency of academic staff at UTHM to incorporate BL into their regular teaching practices.

1.9.9 Hedonic Motivation

Hedonic Motivation (HM) refers to the extent to which an individual experiences enjoyment or pleasure when using a technology (Venkatesh et al., 2012). In this study, HM is operationalised as academic staff's perceived enjoyment of using blended learning (BL) as part of their instructional activities at UTHM.

1.9.10 Pedagogical Knowledge

Pedagogical Knowledge (PK) refers to academic staff's self-perceived understanding of teaching processes, instructional strategies, and assessment approaches relevant to organising and delivering learning activities (Mishra & Koehler, 2006). In this study, PK is conceptualised as a knowledge domain within the TPACK framework that reflects academic staff's perceived capability to plan, adapt, and evaluate teaching-related activities in BL contexts, rather than an observation of pedagogical practice or teaching effectiveness at UTHM.

1.9.11 Performance Expectancy

Performance Expectancy (PE) refers to the degree to which an individual believes that using a system will support task accomplishment or job performance (Venkatesh et al., 2003). In this study, PE refers to academic staff's perceptions of the usefulness of BL in supporting their teaching-related tasks at UTHM.

1.9.12 Social Influence

Social Influence (SI) refers to the extent to which academic staff perceive that important referent groups within the institution, such as colleagues, department heads, faculty management, and university leadership, expect or encourage them to adopt and use BL (Venkatesh et al., 2003). In this study, SI reflects the perceived institutional and professional expectations of UTHM academic staff, rather than the influence of the broader university population.

1.9.13 Technological Knowledge

Technological Knowledge (TK) refers to knowledge of digital technologies and tools relevant to teaching and learning, including hardware, software, and related technological systems (Koehler & Mishra, 2008). In this study, TK represents academic staff's self-perceived knowledge of using digital devices, platforms, and technological resources that support BL at UTHM.

1.9.14 Use Behaviour

Use Behaviour (USE), also referred to as actual use (Venkatesh et al., 2003), represents the current engagement of academic staff with BL in their teaching activities at UTHM.

1.10 Conclusion

This chapter introduces the study by outlining its focus, context, and theoretical grounding, and by establishing the rationale for examining the adoption of BL among academic staff. It presents the background of the study, articulated the research problem, defined the research objectives and framework, and clarified the scope, significance, and key concepts underpinning the investigation.

The subsequent chapters are organised as follows. Chapter 2 presents a review of relevant literature on BL, technology acceptance, and academic staff knowledge, and identifies research gaps that inform the study's framework. Chapter 3 describes the research methodology, including the research design, sampling procedures, instrumentation, and data analysis techniques. Chapter 4 reports the empirical findings in relation to the research questions and hypotheses. Finally, Chapter 5 discusses the findings in light of existing literature and outlines the study's implications, limitations, and recommendations for future research.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

This chapter provides a comprehensive review of three key areas relevant to Blended Learning (BL) and technology acceptance theories. First, it defines BL and explores its implementation within Malaysian higher education, with reference to UTHM. Second, it examines the primary theoretical frameworks underpinning this study, namely UTAUT2 and the TPACK framework, while reviewing relevant past research. Lastly, it presents the conceptual framework and hypotheses, analysing the factors contributing to effective BL practices and their potential impact on enhancing user experience in BL environments.

The challenges Malaysian Higher Education Institutions (HEIs) face in adopting BL are discussed in detail, alongside an in-depth evaluation of BL adoption and use at UTHM. The analysis also highlights the strengths and limitations of existing technology acceptance theories, drawing on recent research to identify gaps and provide further insights.

2.1 Blended Learning Definition

BL is defined in various ways across academic literature, highlighting its growing significance within educational context. The most frequently cited BL definitions in the literature are those proposed by Garrison and Kanuka (2004), cited 3,119 times, followed by Graham (2006), cited 2,149 times (Google Scholar, 25 January 2019). According to Garrison and Vaughan (2008), BL involves a design approach in which online and face-to-face learning complement each other to create an improved educational experience. This perspective aligns with the statement from the president of Pennsylvania State University, who identified the integration of online and traditional instruction as a transformative yet underappreciated trend in higher education (Young, 2002, cited in Graham & Dziuban, 2008). Lynch and Dembo (2004) also describe BL as a form of distributed education that incorporates a mix of technologies and methods to enable both real-time (synchronous) and anytime (asynchronous) interactions among academic staff and students within a course. Although BL is relatively new in academic and corporate contexts (Graham, 2009), it has quickly become a central focus in education.

The terminology surrounding BL has also evolved over time. Graham (2009) noted that hybrid learning was commonly used prior to the emergence of BL, and the two terms are now used interchangeably. Regardless of nomenclature, combining classroom instruction with communication technologies is widely acknowledged as a transformative force in higher education (Garrison & Vaughan, 2008). Graham (2009) defines BL as a system combining face-to-face and technology-mediated instruction, illustrating the integral role of technology in this approach.

Since its introduction in the early 2000s, BL has rapidly gained traction and evolved over time into a widespread phenomenon in higher education (Bonk & Graham, 2006; Garrison & Vaughan, 2008; Rovai & Jordan, 2004; Taylor & Newton, 2013). The adoption of BL marked a significant shift in the field of distance education, blending traditional and online learning to offer more dynamic and flexible educational experiences (Garrison & Kanuka, 2004; Kim et al., 2009; Osguthorpe & Graham, 2003; Rovai & Jordan, 2004; Vaughan, 2007). Despite its growing prevalence, there remains some ambiguity surrounding the term itself. However, widely cited definitions by Garrison and Vaughan (2008) and Graham (2006) have provided clarity.

Garrison and Vaughan (2008) define BL as "the thoughtful integration of classroom face-to-face learning experiences with online learning experiences" (p. 96), while Graham (2006) describes it as the combination of traditional face-to-face learning with computer-mediated instruction (Figure 2.1). Both definitions emphasise the interdependence of these two components in creating a cohesive and integrated learning experience.

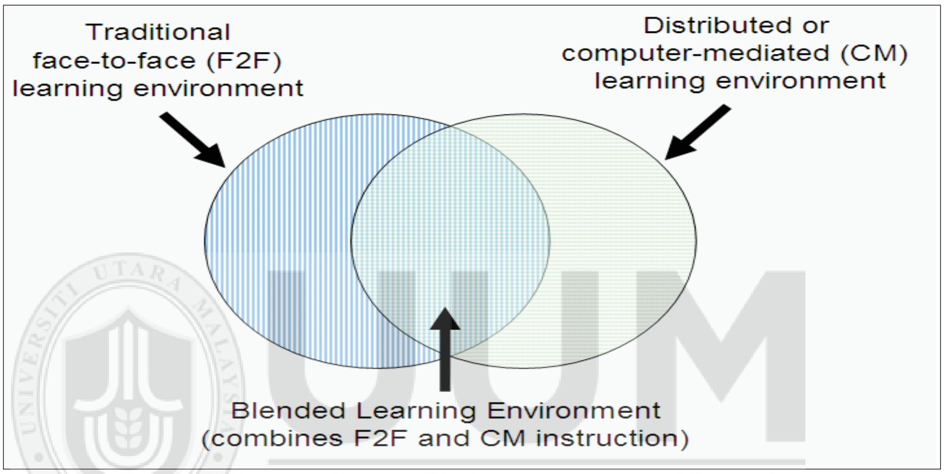

Figure 2.1 Blended Learning Combines Traditional Face-To-Face
Source: Graham, C. R. (2009).

Graham (2011) further classified BL into three models: enabling, enhancing, and transforming. Each model reflects varying levels of integration and transformation in teaching practices, illustrating the versatility and adaptability of BL in meeting diverse educational needs. This classification underscores the importance of intentional implementation, in which academic staff strategically combine traditional and online elements to maximise learning outcomes. As BL continues to evolve, it remains a powerful approach for addressing the challenges of modern education and leveraging the strengths of both face-to-face and digital learning environments.

2.1.1 Enabling Blends

Enabling blends represent a digital extension of traditional classes, offering students additional learning opportunities and flexibility through online tools. This model functions as an add-on and does not alter the underlying pedagogy (Lindquist, 2012). For example, students who miss class or require revision can access recordings of face-to-face lectures, including presentation slides and audio or video content.

2.1.2 Enhancing Blends

Enhancing blends involves modifying teaching and learning pedagogy, such as reducing class time and integrating online components (Graham, 2006, 2011). This model treats online learning as an additional option for students, complementing face-to-face classes. Modifications often include replacing traditional lectures with interactive multimedia presentations, reducing in-class time by approximately 30 minutes, and allocating more time for group work during class sessions, rather than relying on academic staff-led presentations. Enhancing blends also encourage students to provide feedback or suggestions to their peers. This model is the most widely adopted type of BL (Graham, 2011; Sharpe, Benfield, Roberts, & Francis, 2006).

2.1.3 Transforming Blends

Transforming blends represent a significant pedagogical shift, leveraging the full capabilities of web-based technology to support active learning. This model offers the most significant benefits but requires a substantial re-evaluation of traditional pedagogical methods by higher education institutions (Benson, Anderson, & Ooms, 2011). In transforming blends, students actively construct knowledge and skills, moving beyond the role of passive recipients. Significant changes in face-to-face learning activities are necessary to support the effective integration of online learning. The harmonious combination of traditional and online teaching strategies forms the core of this model, described as the "thoughtful fusion" of modalities (Garrison & Vaughan, 2008, p. 5).

BL has emerged as a prominent educational approach in the 21st century, combining the best aspects of face-to-face instruction with online learning experiences. Garrison and Vaughan (2008) define BL as "the thoughtful integration of classroom face-to-face learning experiences with online learning experiences" (p. 96). This innovative approach has gained significant traction in higher education institutions worldwide, offering a flexible and engaging learning environment that caters to diverse student needs.

2.1.4 Blended Learning Models

BL models have evolved to accommodate diverse educational contexts and objectives, ranging from enhancing learning effectiveness to increasing convenience. Graham (2009) identifies four distinct levels at which BL can occur: institutional, programme, course, and activity levels.

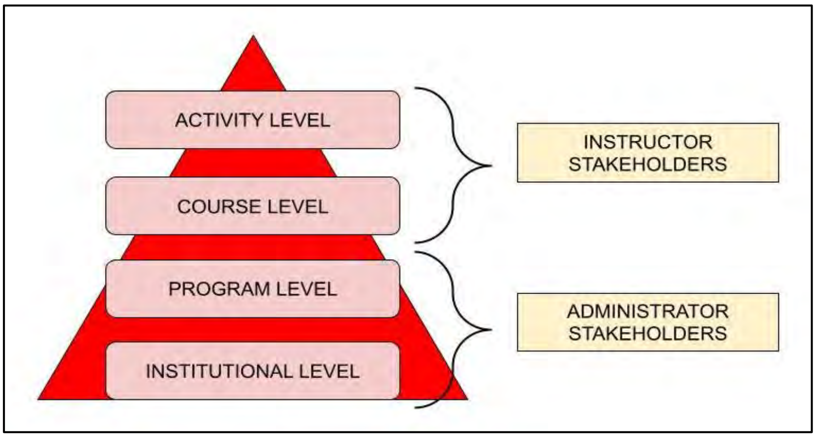

Figure 2.2 Different Levels of Blended Learning

Source: Graham, C. R., & Allen, S. (2009).

Figure 2.2 shows that each level caters to different stakeholders and priorities, with course-level and activity-level models primarily focused on learning effectiveness and productivity. At the same time, programme-level and institutional-level blending often addresses cost-effectiveness and expanded access to education.

Table 2.1
Description of Different Levels of Blends

Levels of Blends	**Description**
Activity-Level Blend	An instructional activity includes both online and face-to-face components.
Course-Level Blend	A course that involves students in both online and face-to-face activities.
Programme-Level Blend	A programme that allows or requires a mix of on-campus and online courses for programme completion.
Institutional-Level Blend	Institutional blending requirements or support for BL options.

(Graham, C. R., & Allen, S., 2009).

At the course-level, instructors can integrate online and face-to-face instruction within a single course design. Kenney and Newcombe (2011) suggest that faculty can effectively employ multiple approaches to blend these two modalities. Face-to-face sessions can be utilised to develop a deeper understanding of the material through interactive discussions, synthesis of concepts, and real-world applications (Collopy & Arnold, 2009). This approach allows for more meaningful engagement with the content and fosters the development of critical thinking skills.

Smart and Cappel (2006) propose several strategies for implementing BL at the course-level. One approach involves students completing online units before class meetings to establish a shared foundational knowledge base. This preparation enables in-class sessions to delve deeper into application exercises and problem-solving activities. Alternatively, e-learning components can be employed after class meetings to maintain ongoing dialogue among participants through online chats or discussion board postings. Some BL models may incorporate pre- and post-class e-learning elements to create a more comprehensive learning experience.

Graham (2009) describes that the activity-level blend incorporates face-to-face and computer-mediated elements within a single learning activity. This granular approach allows instructors to tailor specific activities to leverage the strengths of both modalities, potentially enhancing student engagement and learning outcomes.

At the programme-level blending, BL often involves a mix of fully online and face-to-face courses within a degree programme. This approach provides students with flexibility while maintaining some traditional classroom experiences. Institutional-level blending, on the other hand, may involve broader initiatives that affect the entire educational institution, such as offering a combination of online and on-campus learning experiences across multiple programmes.

It is important to note that the effectiveness of BL models can vary depending on the specific context, subject matter, and student needs. As such, ongoing research and evaluation are crucial to refining and improving BL approaches across all levels of implementation.

BL is characterised by the integration of synchronous and asynchronous learning activities, the incorporation of digital technologies alongside traditional classroom methods, flexible access to learning materials, and a greater emphasis on student-centred learning (Graham, 2006). These elements create a more personalised and adaptive learning experience, catering to the diverse and evolving needs of modern learners.

One of the significant benefits of BL is its capacity to harness technology to enhance the learning process. Boelens et al. (2017) highlight that this approach effectively combines the advantages of face-to-face and online learning activities, allowing for greater flexibility in terms of time, location, and learning pace. This adaptability is particularly beneficial for students with varying schedules and learning preferences.

The integration of digital technologies in BL has given rise to various instructional models. The flipped classroom, for example, requires students to engage with online content before attending in-person sessions. Research by Thai et al. (2017) suggests that this model has a positive impact on learning performance and student satisfaction in higher education. By shifting direct instruction outside the classroom, face-to-face sessions can focus on interactive and collaborative activities, fostering deeper engagement and comprehension.

BL also plays a role in enhancing student motivation and self-regulated learning. Boelens et al. (2018) suggest that these environments offer students greater control over their learning process, promoting autonomy and improved learning outcomes. This approach supports academic success and helps students develop essential self-directed learning skills, which are crucial for lifelong learning.

As BL advances, researchers and academic staff continue to explore strategies to maximise its effectiveness. Learning analytics and adaptive technologies are becoming more prevalent in these environments. Dziuban et al. (2018) emphasise that learning analytics can provide valuable insights into student engagement and performance, enabling more targeted interventions and personalised support to enhance learning outcomes.

2.2 Evolution of Blended Learning in Higher Education

This section examines the evolution of BL within higher education, tracing its development from traditional face-to-face instruction and early e-learning systems to more integrated learning environments that combine physical and digital modes of delivery. The discussion focuses on the conceptual development of BL, its theoretical foundations, and the challenges associated with its implementation, thereby providing context for understanding the adoption of BL in contemporary higher education.

2.2.0 Conceptual Development of Blended Learning

Learning is commonly understood as a process that involves the acquisition of knowledge, skills, and competencies, which contribute to changes in learners' understanding and capability (Kuhlthau, 2010; Wirth & Perkins, 2008). In higher education, early conceptualisations of learning outcomes were shaped by frameworks such as Bloom's Taxonomy (1956) and later refinements, including Biggs's SOLO taxonomy (Biggs, 2007), which emphasise levels of cognitive complexity. These perspectives provide an important foundation for subsequent developments in technology-supported learning environments.

Traditional face-to-face learning environments have long been regarded as the cornerstone of formal education due to their emphasis on direct interaction and immediate feedback between academic staff and students. However, advances in ICTs have progressively transformed educational contexts, leading to the emergence of e-learning systems that utilise web-based platforms, mobile applications, and multimedia tools (Almarabeh & Mohammad, 2013). Early work highlighted the role of technological infrastructure in supporting the acquisition, transfer, and application of information within educational settings (Brooks, 2000). As a result, e-learning environments have been increasingly adopted to extend access to learning resources and facilitate communication and collaboration beyond the physical classrooms (Eison, 2010; Warger & Dobbin, 2009).

Despite these developments, research has identified limitations associated with fully online learning, particularly in relation to interpersonal interaction and sustained student engagement when compared to traditional face-to-face instruction (Ya Ni, 2012; Eison, 2010). In response to these limitations, BL emerged as an approach that combines face-to-face instruction with online learning components in a more integrated and deliberate manner (Graham, 2013; Garrison & Vaughan, 2008). Rather than replacing existing instructional modes, BL represents an attempt to draw on the strengths of both physical and digital learning environments.

Since its early conceptualisation, BL has evolved alongside advances in educational technology. Initial implementations involved integrating classroom teaching with distributed and computer-mediated learning environments, supported by advancements in networked communication and digital platforms (Graham, 2006). Early technology-based training systems, such as PLATO, demonstrated the potential of integrating instructional content with computer-supported interaction, thereby laying the conceptual groundwork for later BL models in higher education (Alavi & Leidner, 2001; Graham, 2006).

In recent decades, BL has become increasingly visible in higher education institutions worldwide as universities expand their use of digital platforms and LMS. Prior studies suggest that combining face-to-face and online components may offer greater flexibility in instructional delivery and accommodate diverse learning preferences and needs (Lim & Morris, 2009). The widespread adoption of remote and hybrid learning during the COVID-19 pandemic further accelerated the normalisation of BL approaches within higher education contexts (Trotter & Qureshi, 2023).

Overall, the conceptual development of BL reflects a gradual shift from traditional classroom-based instruction towards more integrated learning environments that incorporate digital technologies. This evolution provides important context for examining how academic staff engage with BL, particularly in relation to their acceptance of technology and knowledge readiness, which form the focus of the present study.

2.2.1 Theoretical Foundations of Blended Learning

Several learning theories have been used to explain and contextualise BL environments, although they do not directly inform the analytical framework adopted in this study. The early theoretical foundations of BL can be traced to educational frameworks such as Computer-Supported Collaborative Learning (CSCL). CSCL emphasises the role of technology in supporting collaborative knowledge construction through computer-mediated interaction (Koschmann, 2002). These principles have influenced the development of BL approaches that integrate face-to-face instruction with digital learning environments (Powell et al., 2015).

Building on CSCL, contemporary BL environments are commonly associated with constructivist and social learning theories, which emphasise active participation, interaction, and collaborative knowledge construction (Garrison & Vaughan, 2008). One prominent framework derived from these perspectives is the Community of Inquiry (CoI) framework (Garrison & Vaughan, 2008), which conceptualises learning experiences through the interaction of cognitive presence, social presence, and teaching presence in online and blended learning contexts. The CoI framework has been widely used to describe learning dynamics in BL environments, particularly in relation to learner interaction and engagement.

Despite the increasing prevalence of computer-mediated communication in higher education, prior studies indicate that technology alone cannot fully substitute for face-to-face interaction, especially in distance or fully online learning settings (Olson, 2002; Warger & Dobbin, 2009). In this regard, BL has been conceptualised as an approach that combines physical and digital modes of instruction to balance interaction, flexibility, and access to learning resources (Powell et al., 2015; Ya Ni, 2012).

The implementation of BL has been discussed in the literature as requiring alignment across multiple dimensions, including institutional support, technological infrastructure, and instructional considerations (Porter et al., 2014; Bonk & Graham, 2006). In higher education contexts, such alignment is often highlighted as important due to the diversity of learners and delivery modes involved (Halverson et al., 2014). However, these discussions primarily serve to contextualise BL environments rather than to explain individual technology adoption behaviour.

While these theories and models provide valuable conceptual insights into how BL environments function, they are not employed as the analytical framework of the present study. Instead, this study adopts UTAUT2 and the TPACK framework to examine academic staff technology acceptance and knowledge readiness for BL adoption.

2.2.2 Implementation Challenges and Opportunities

The implementation of BL in higher education presents both opportunities and challenges that require careful and strategic institutional consideration. Prior studies have identified potential advantages such as increased flexibility and extended access to learning resources, alongside challenges related to technological readiness, academic staff support, and institutional coordination (Garrison & Vaughan, 2008; Moskal et al., 2013).

Research suggests that the effectiveness of BL implementation is influenced by several contextual factors, including institutional strategy, the availability of support structures, and the preparedness of academic staff to engage with digital technologies (Porter & Graham, 2016). While some studies have associated the adoption of BL with improved student satisfaction and instructional efficiency, such outcomes are highly dependent on the alignment between institutional policies, technological infrastructure, and academic staff readiness (Dziuban et al., 2018; Graham et al., 2013).

At the same time, the literature consistently highlights persistent challenges associated with BL implementation. These challenges include ensuring adequate technological infrastructure, providing sustained professional development, and maintaining consistency across different modes of delivery (Moskal et al., 2013). In particular, academic staff engagement has been identified as a critical factor, as teaching in BL environments requires familiarity with digital platforms and confidence in integrating online components into existing teaching responsibilities (Vaughan, 2007; So & Bonk, 2010).

Furthermore, studies emphasise that BL implementation is not uniform across contexts and often requires adaptation to specific institutional conditions and disciplinary requirements (Hrastinski, 2019). Rather than adopting standardised models, institutions are encouraged to consider local readiness, available support mechanisms, and academic staff capability when implementing BL initiatives.

Overall, the literature indicates that while BL offers opportunities for flexible and technology-enhanced learning, its successful implementation depends less on the availability of technology alone and more on institutional support and academic staff readiness. These considerations underscore the importance of examining BL adoption from the perspective of academic staff acceptance and knowledge readiness, which forms the focus of the present study.

2.2.3 Emerging Trends in Blended Learning

Recent literature suggests that BL continues to evolve in tandem with advancements in digital technologies and shifts in higher education delivery models. Developments such as learning analytics, adaptive learning systems, and data-informed instructional platforms have been discussed as having the potential to influence the design and management of BL environments (Johnson et al., 2016). At the same time, researchers caution that technological advancement alone does not guarantee effective learning, emphasising the need to balance innovation with sound pedagogical principles (Garrison & Vaughan, 2008).

As higher education institutions expand their use of BL, greater attention has been directed towards issues such as instructional alignment, academic staff development, and appropriate assessment practices within BL environments (Picciano, 2009;

Vaughan et al., 2013). These discussions highlight that the sustainability of BL initiatives depends not only on emerging technologies but also on institutional readiness and academic staff capability.

Accordingly, recent studies suggest that future research should focus less on technological novelty and more on understanding how institutional support, technology acceptance, and academic staff knowledge influence the long-term adoption of BL in higher education contexts (Garrison & Vaughan, 2008). This perspective provides a rationale for examining BL adoption through acceptance- and knowledge-based frameworks, as undertaken in the present study.

2.3 A Global Perspective

BL has gained widespread recognition globally as a pedagogical approach that integrates face-to-face instruction with online learning modalities. It is widely acknowledged for its flexibility, adaptability, and potential to enhance learning effectiveness across diverse educational contexts (Garrison & Vaughan, 2008; Means et al., 2013). The COVID-19 pandemic further accelerated the adoption of BL as educational institutions worldwide sought to maintain instructional continuity while addressing health and safety concerns (Dhawan, 2020). As a result, BL has become an established feature of contemporary education, although its implementation continues to vary across regions depending on factors such as technological infrastructure, institutional readiness, and policy environments.

2.3.0 Adoption in Developed Countries

In developed countries such as the United States, the United Kingdom, and Australia, BL has been widely adopted, particularly within higher education institutions. These contexts are characterised by relatively advanced digital infrastructure, strong institutional support, and systematic integration of online and face-to-face instructional components, often described as transformative blends (Graham et al., 2019). In the United States, BL has become a mainstream instructional approach in higher education, driven by institutional strategies aimed at enhancing flexibility and instructional effectiveness (Allen & Seaman, 2017; Picciano, 2021). Similarly, universities in the United Kingdom have increasingly incorporated BL models, with a focus on developing digital capabilities and enhancing student engagement (Office for Students, 2022).

Australian universities have also demonstrated strong uptake of BL, implementing hybrid and flipped classroom approaches that combine synchronous and asynchronous learning activities (Bond et al., 2021). These developments suggest that, within developed contexts, the adoption of BL is supported not only by technological readiness but also by institutional policies, organisational support, and professional practices that enable educators to integrate digital tools meaningfully into their teaching.

2.3.1 Challenges and Progress in Developing Countries

In developing countries, the adoption of BL has generally progressed from enabling or enhancing blends towards more structured implementation models, although this transition is often constrained by infrastructural, financial, and human resource limitations (Singh & Thurman, 2019). While access to digital platforms has expanded, disparities in connectivity, device availability, and institutional capacity continue to shape uneven implementation outcomes.

Within the Asian context, countries such as India and Malaysia have demonstrated notable progress in the adoption of BL, largely driven by national education policies and sustained investments in digital infrastructure. India’s National Education Policy (NEP) 2020 explicitly promotes the integration of technology and BL approaches to enhance access, flexibility, and educational quality (Ministry of Education, India, 2020). Similarly, Malaysia’s Education Blueprint 2013–2025 has encouraged higher education institutions to embed BL within teaching and learning practices, with several public universities actively supporting digital and BL initiatives (Aziz et al., 2022).

Despite these policy-driven advancements, empirical studies consistently report persistent challenges at the implementation level. These include academic staff resistance to technology-related change, limited professional development opportunities, and unequal access to technological resources among academic staff (Wan & Nasri, 2023). Such challenges indicate that institutional readiness and infrastructure alone are insufficient to ensure effective BL adoption, underscoring the importance of examining individual-level factors related to technology acceptance and pedagogical–technological competence, which are central to the present study.

Recent global developments, particularly those triggered by the COVID-19 pandemic, have further reinforced the strategic importance of BL in ensuring flexibility, resilience, and continuity in higher education (UNESCO, 2021). While emerging technologies and innovative credentialing models continue to shape future educational possibilities, prior research suggests that the effectiveness and sustainability of BL implementation depend less on technological sophistication and more on educators’ readiness, acceptance, and knowledge-related capacity to integrate digital tools meaningfully into teaching practice (Zawacki-Richter & Marín, 2020; Trucano, 2023). These observations underscore the need to move beyond technology-centred discussions and to examine the individual-level acceptance and knowledge-related factors that influence the adoption of BL among academic staff.

2.4 Blended Learning in Asia

Previous studies indicate that BL implementation in many Asian contexts initially adopts enabling or enhancing blends, where digital technologies are used primarily to support or supplement traditional face-to-face instruction (Latchem et al., 2008; Reeves, 2009; Tham & Tham, 2011; Tue & Duyen, 2010; Zhao & McConnell, 2006). Early implementations in countries such as Singapore, Japan, and Vietnam commonly involved uploading lecture materials, recorded content, or substituting limited online hours for conventional classroom sessions (Tham & Tham, 2011; Tue & Duyen, 2010). These approaches were often constrained by a strong reliance on traditional instructional practices and limited understanding of BL principles among academic staff (Lefoe & Hedberg, 2006; Verkroost et al., 2008; Zhao & McConnell, 2006).

More recent research, however, suggests that the BL landscape in Asia has undergone considerable evolution, particularly within higher education contexts. A comprehensive study by Tan et al. (2022) highlights that the implementation of BL in Malaysia and the wider Asian region has become more widespread and structured, driven by its flexibility and relevance to diverse disciplinary contexts. Nevertheless, the study also notes that much of the existing BL research in Asia continues to focus on students' perspectives, with comparatively limited attention given to academic staff readiness, knowledge development, and technology integration capability.

The COVID-19 pandemic further accelerated BL adoption across Asian higher education institutions, prompting rapid shifts to online and hybrid instructional models (UNESCO, 2021). While this transition strengthened digital infrastructure and institutional support, empirical evidence suggests that persistent challenges remain, particularly in relation to academic staff digital competence, confidence in technology use, and access to sustained professional development (Lim & Wang, 2023). These findings suggest that, despite policy support and technological advancement, effective BL adoption in Asia continues to depend heavily on educators' acceptance of technology and their ability to integrate it meaningfully into teaching practice.

2.5 Blended Learning in Malaysian HEIs

National education policies in Malaysia have consistently emphasised the role of information and communication technologies (ICT) in higher education teaching and learning. The Malaysia Education Blueprint 2015–2025 (Higher Education) formalised this direction by promoting the systematic adoption of BL as a means of enhancing instructional flexibility, access, and quality (Ministry of Education Malaysia, 2015; Ministry of Higher Education, 2018). Within this policy context, BL is commonly understood as the intentional integration of face-to-face instruction with online learning components, rather than the replacement of conventional classroom teaching.

In line with this national direction, BL in Malaysian higher education is generally conceptualised as the integration of physical and digital learning environments to support instructional delivery, learner interaction, and access to learning resources (Garrison & Vaughan, 2008; Riley et al., 2013). This conceptualisation aligns with the operational definition adopted in the present study, which treats face-to-face and online modes as a unified instructional approach, rather than as separate delivery systems.

The adoption of technology-supported learning in Malaysian higher education predates the formal introduction of BL policies. Since the late 1990s, public and private universities have implemented e-learning platforms, LMS, and distance education initiatives to support flexible and technology-enhanced learning (Asirvatham et al., 2006; Haron et al., 2012). These early developments indicate that Malaysian HEIs have long possessed experience with digital learning infrastructure and online instructional tools.

However, the availability of digital infrastructure does not necessarily translate into consistent or sustained adoption of BL among academic staff. Recent studies indicate that although LMS platforms and online learning systems are widely accessible across Malaysian HEIs, their instructional utilisation varies considerably across institutions and disciplines (Chan et al., 2022; Sazeli et al., 2024). Research conducted during and after the COVID-19 pandemic further revealed disparities in academic staff readiness, confidence, and engagement with BL approaches, despite increased institutional reliance on digital platforms (Yusoff et al., 2021; Ali et al., 2023).

Empirical evidence suggests that challenges in BL adoption within Malaysian HEIs are frequently associated with academic staff–related factors, including technological confidence, workload concerns, adequacy of training, and perceptions of institutional support (Chung et al., 2020; Yahaya & Mohd Jawi, 2020). These findings suggest that BL adoption is influenced not only by policy directives and technological availability, but also by individual-level technology acceptance and knowledge-related considerations.

Overall, the literature demonstrates that BL has been institutionally promoted and structurally supported within Malaysian higher education for several decades. Nevertheless, variations in academic staff engagement and sustained use highlight the need to examine BL adoption beyond infrastructure provision alone. This underscores the importance of investigating technology acceptance and technological–pedagogical knowledge readiness among academic staff, which constitutes the central focus of the present study.

2.5.1 Historical Development of E-Learning in Malaysia

The development of e-learning in Malaysian higher education has occurred progressively over several decades. Early initiatives can be traced to the late 1990s, when public universities such as Universiti Malaya (UM) began using LMS to support online course delivery (Asirvatham et al., 2006). Shortly thereafter, institutions including Universiti Sains Malaysia (USM) and Universiti Putra Malaysia (UPM) incorporated information technology into their distance education initiatives, while Multimedia University (MMU) was established with a strong emphasis on information and communication technology (ICT)–enabled teaching and institutional management (Asirvatham et al., 2006; Bunyarit, 2006). These developments reflect early institutional engagement with technology-supported learning in Malaysia.

Throughout the early 2000s, additional universities adopted e-learning platforms to expand access to higher education. Open University Malaysia (OUM) implemented an e-learning system in 2001 to support adult and distance learners, followed by

Universiti Utara Malaysia (UUM), which adopted e-learning in 2003 and later integrated the Moodle learning management system in 2010 (Haron et al., 2012). The adoption of BL approaches became more visible in subsequent years, with institutions such as the International Islamic University Malaysia (IIUM) formally incorporating BL into their instructional models by 2011 (Haron et al., 2012).

At the policy level, the Malaysia Education Blueprint 2015–2025 (Higher Education) marked a significant milestone by formally positioning blended and flexible learning as key strategies for higher education transformation (Ministry of Education Malaysia, 2015; Ministry of Higher Education Malaysia, 2018). The blueprint articulated national targets for BL delivery and emphasised strengthening digital infrastructure and academic staff capability. In response, institutions such as Universiti Tun Hussein Onn Malaysia (UTHM) introduced institutional initiatives, including full online and blended learning frameworks, to support the integration of online and face-to-face teaching modalities.

The COVID-19 pandemic in 2020 further accelerated the adoption of e-learning across Malaysian higher education, as universities transitioned to fully online delivery during the emergency remote teaching period (Rahim et al., 2021; Yusoff et al., 2021). This period led to a widespread reliance on LMS platforms and video-conferencing tools, as well as an increased institutional dependence on digital teaching systems (Ali et al., 2021). Subsequently, the Ministry of Higher Education continued to emphasise hybrid and flexible learning models as part of post-pandemic higher education planning (Ministry of Higher Education Malaysia, 2021, 2023).

Overall, the historical development of e-learning in Malaysia demonstrates that digital learning infrastructure and policy support have been progressively established over time. However, empirical research suggests that the presence of technology and institutional initiatives alone does not necessarily ensure consistent or sustained adoption of BL among academic staff (Yeop et al., 2016; Ghazali et al., 2018). This highlights the importance of examining individual-level factors, including technology acceptance and knowledge readiness, which are central to the present study.

2.5.2 Current State and Challenges of Blended Learning in Malaysian HEIs

Building on the established digital infrastructure and policy support outlined in the preceding section, the current BL landscape in Malaysian higher education reflects both notable institutional progress and persistent implementation challenges. Although BL has been increasingly promoted at national and institutional levels, its adoption and instructional application remain uneven across universities, faculties, and academic disciplines.

Empirical studies report considerable variation in how BL is defined and implemented within Malaysian HEIs. Differences in institutional interpretations of BL, levels of formalisation, and instructional approaches have been documented, complicating efforts to ensure consistency and sustainability of BL practices (Yeop et al., 2016). In many contexts, BL remains limited to the supplementary use of online platforms rather than being fully embedded within instructional design and delivery strategies.

Several infrastructural and human-related challenges continue to hinder the effective implementation of BL. Limitations in technological infrastructure, including system reliability and access to digital resources, have been identified as ongoing constraints in certain institutions (Azhari & Ming, 2015). In addition, variations in digital literacy among academic staff and students influence the extent to which BL tools are utilised meaningfully in teaching and learning contexts (Lim et al., 2019). Transitioning from traditional instructional approaches to BL also requires academic staff to adopt new technology-supported roles and modes of content delivery, which has been reported as a significant challenge in Malaysian higher education settings (Ghazali et al., 2018).

At the policy level, the Malaysia Education Blueprint 2015–2025 (Higher Education) represents a strategic effort to promote ICT integration and BL across HEIs. However, empirical evidence suggests that institutional implementation is shaped more by local capacity, academic staff readiness, and the availability of sustained support mechanisms than by policy intent alone (Yeop et al., 2016; Chung et al., 2020). This suggests that policy endorsement, although necessary, is insufficient to ensure the effective and sustained adoption of BL.

The COVID-19 pandemic further accelerated the use of digital platforms across Malaysian HEIs, resulting in widespread exposure to online teaching tools and LMS among academic staff (Rahim et al., 2021). While this period expanded the scope of technology use, subsequent studies indicate that emergency remote teaching experiences do not automatically translate into sustained or instructionally effective BL practices in the post-pandemic context (Yusoff et al., 2021).

More recent research continues to highlight challenges related to academic staff readiness, resistance to technology-related change, workload concerns, and disparities in institutional resources (Ismail et al., 2021; Seong et al., 2022; Ministry of Higher Education Malaysia, 2023). Collectively, these findings suggest that the adoption of

BL in Malaysian higher education is influenced by factors beyond technological availability and is closely linked to academic staff technology acceptance, confidence, and knowledge readiness.

2.5.3 Implications for Blended Learning Adoption among Academic Staff

The literature on BL in Malaysian higher education consistently indicates that successful adoption depends not only on institutional infrastructure and policy initiatives but also on individual-level factors related to academic staff (Ghazali et al., 2018; Chung et al., 2020). Despite long-standing investments in digital platforms and formal policy support, variations in engagement and sustained use of BL among educators remain evident across institutions.

Existing studies emphasise that academic staff play a central role in determining whether BL is adopted and sustained, as they are responsible for making decisions related to technology use and integration within their teaching contexts. Factors such as perceived usefulness of BL, perceived ease of using digital systems, confidence in handling educational technologies, and access to professional development opportunities have been identified as influential in shaping educators' willingness to adopt BL approaches (Venkatesh et al., 2012; Scherer et al., 2019).

Furthermore, research suggests that disparities in technology-related knowledge among academic staff contribute to uneven adoption of BL across Malaysian HEIs. While some educators demonstrate higher levels of knowledge readiness in relation to content, pedagogy, and technology domains as conceptualised by the TPACK framework, others report lower levels of confidence and familiarity with these knowledge components, which may limit their intention to adopt BL consistently

(Koehler et al., 2013; Lim & Wang, 2023). Importantly, this study does not examine pedagogical practice or instructional strategies; rather, it focuses on educators' knowledge components as antecedents to BL adoption.

These observations highlight a critical gap in the existing literature, particularly with regard to empirical investigations that systematically examine BL adoption from the perspective of academic staff using both acceptance-based and knowledge-based factors. Although prior research has documented infrastructural challenges and policy developments, comparatively less attention has been given to understanding how technology acceptance and educators' knowledge components jointly influence behavioural intention and actual use of BL.

Accordingly, there is a clear need for a theoretically grounded and empirically robust framework that captures both acceptance-based and knowledge-based determinants of BL adoption among academic staff in Malaysian higher education. Addressing this gap provides the rationale for the present study, which integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Technological Pedagogical Content Knowledge (TPACK) framework, with TPACK operationalised explicitly as a framework of knowledge components rather than pedagogical practice.

2.5.4 Government and Institutional Support for Blended Learning

The Malaysian government has introduced a range of national policies and initiatives to promote the systematic integration of BL within higher education institutions. Central to these efforts is the Malaysia Education Blueprint 2015–2025 (Higher Education), which outlines strategic directions for strengthening the use of information and communication technology (ICT) in teaching and learning and positions BL as a key mechanism for enhancing flexibility, access, and educational quality (Ministry of Education Malaysia, 2015).

Complementing this blueprint, the National e-Learning Policy (DePAN 2.0) provides a structured framework for implementing and monitoring BL practices across Malaysian higher education institutions. DePAN 2.0 formalises BL as a key performance indicator for online learning delivery and distinguishes between supportive and replacement BL models, thereby offering institutions a common reference for planning and evaluation (Ministry of Higher Education Malaysia, 2011; Ghazali & Nordin, 2019).

In response to these national initiatives, many Malaysian universities have established dedicated e-learning or digital learning units to support academic staff in implementing BL. These units typically collaborate with institutional information technology departments to provide technical assistance, training programmes, and LMS support (Hussin et al., 2012). More recent national development plans, including the Twelfth Malaysia Plan (2021–2025), have further reinforced the role of technology-supported learning across higher education and technical and vocational education and training sectors (Economic Planning Unit, 2021).

Despite sustained policy attention and institutional investment, empirical evidence suggests that government and institutional support alone do not guarantee consistent or effective BL adoption at the individual academic staff level. The translation of national strategies into everyday teaching practice remains highly dependent on academic staff technology acceptance, confidence, and knowledge readiness. This policy-practice gap underscores the importance of examining BL adoption from the perspective of academic staff, which forms the central focus of the present study.

2.6 Blended Learning in UTHM

In alignment with national higher education policies, UTHM has implemented various initiatives to support the systematic integration of BL within its teaching and learning practices. At UTHM, BL is generally conceptualised as the integration of face-to-face instruction with online learning activities facilitated through institutional digital platforms. To support this approach, the university has invested in LMS, digital library resources, and multimedia delivery platforms to provide the necessary technological infrastructure for the implementation of BL.

UTHM's engagement with e-learning began in the late 1990s with the adoption of an LMS to support teaching and learning activities. Over time, limitations related to system functionality and integration prompted the university to transition towards an institution-specific LMS. In January 2011, UTHM introduced the Academic Online Resources (AUTHOR) system as its primary LMS to support online and BL activities.

To contextualise the institutional learning environment at UTHM, Figure 2.3 illustrates the AUTHOR learning management system, which serves as the primary platform supporting BL activities.

AUTHOR was designed to address the limitations of previous LMS platforms by integrating teaching, learning, and administrative systems within a single environment. Through AUTHOR, academic staff can upload learning materials, manage assessments, and facilitate both synchronous and asynchronous interactions with students. The system also provides monitoring and reporting functions to support institutional oversight of online learning activities.

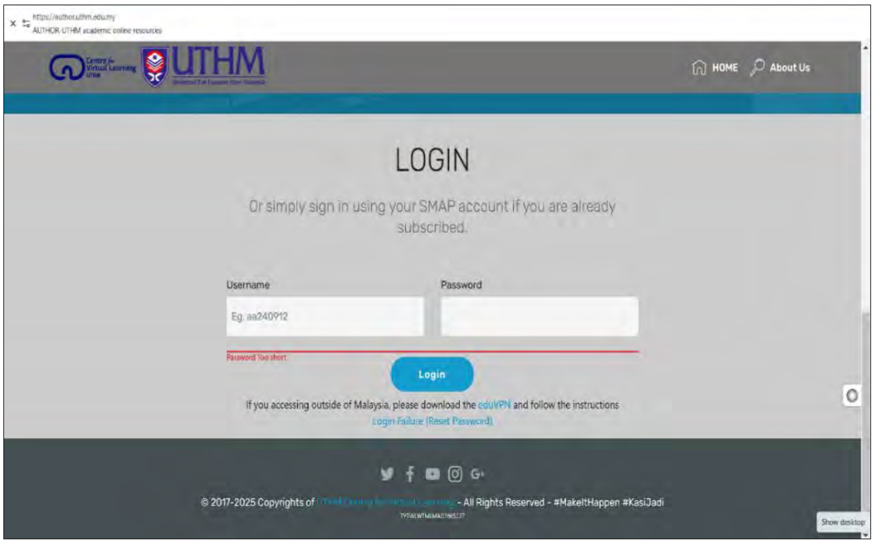

Figure 2.3 UTHM Author System Login Interface

Figure 2.4 presents an example of the AUTHOR interface to illustrate the digital environment through which academic staff are expected to manage teaching materials, assessments, and online interactions.

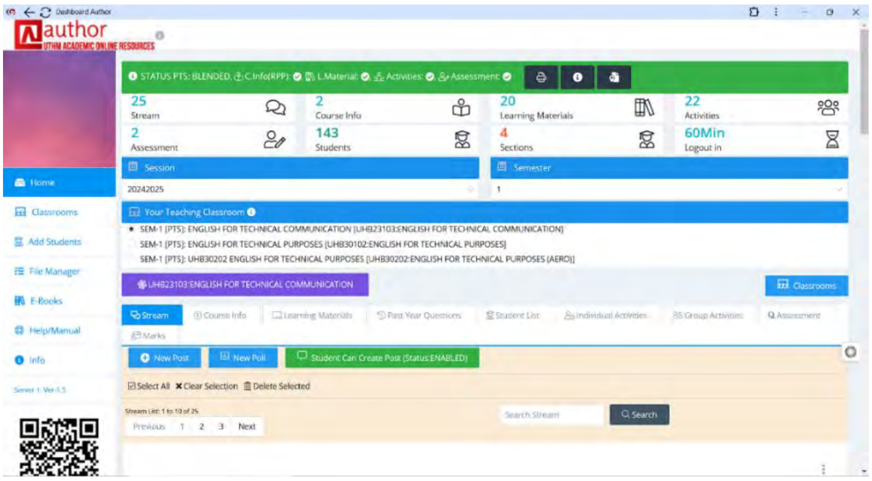

Figure 2.4 UTHM Author System After Login Interface

These figures are included to provide contextual understanding of the institutional digital environment and do not imply the extent or effectiveness of BL adoption among academic staff.

To further strengthen the implementation of BL, UTHM established the Centre for Global Online Learning (GLOBAL) in 2016. GLOBAL plays a central role in coordinating e-learning initiatives, providing training, and supporting academic staff in the development of online and blended instructional materials. In addition, initiatives such as the Full Online Classroom (FOC) were introduced to familiarise academic staff and students with online teaching and learning environments and to encourage engagement with digital platforms.

Despite these institutional efforts, prior research suggests that the adoption and sustained use of BL at UTHM remain uneven. Studies conducted within the UTHM context indicate that while digital platforms and training opportunities are available, academic staff engagement with BL varies depending on factors such as technological confidence, perceived usefulness, workload considerations, and familiarity with online teaching systems (Kirin et al., 2021; Ahmad et al., 2024). These findings suggest that institutional infrastructure alone does not guarantee consistent or sustained adoption of BL.

Existing research on BL at UTHM has predominantly focused on students' perspectives, including their readiness, engagement, and experiences with online and BL environments (Abdul Kadir, 2023; Kepar & Nasuredin, 2023; Zainal & Salim, 2024). While these studies provide valuable insights into student experiences, comparatively limited empirical attention has been given to academic staff perspectives, particularly regarding their technology acceptance and knowledge readiness for BL integration.

Given the central role of academic staff in designing and delivering BL, understanding the factors that influence their adoption and sustained use of BL is critical. The limited focus on academic staff technology acceptance and knowledge-related factors within the UTHM context highlights a clear research gap. Addressing this gap is essential for informing institutional strategies that support the sustainable implementation of BL at UTHM, which is the focus of the present study.

2.7 Barriers to Adoption of BL in Higher Education Institutions

Previous studies have identified a wide range of factors influencing academic staff adoption of technology-enhanced teaching approaches, including motivation, perceptions, attitudes, collaboration, technology-related reasoning, and individual characteristics (Uluyol & Şahin, 2016; Ibieta et al., 2017; Drossel et al., 2017; Heitink et al., 2016; Gil-Flores et al., 2017). Within the context of BL, these factors are commonly discussed as barriers that hinder effective and sustained adoption. The literature generally categorises such barriers into institutional-related and individual-related challenges (Rolfe et al., 2008).

2.7.0 Institutional Barriers

Institutional barriers remain among the most frequently reported constraints in BL adoption. These barriers include limitations in technological infrastructure, inadequate technical support, insufficient training provision, and unclear institutional policies related to online teaching and technology integration (Gambari & Okoli, as cited in Onasanya et al., 2010; Newton, 2003; Nichols, 2008; Sife et al., 2007). Several studies have highlighted that a lack of leadership support and coordinated institutional strategies can discourage academic staff from engaging meaningfully with BL initiatives (Findik Coşkunçay & Özkan, 2013; Mtebe & Raisamo, 2014).

Time constraints and workload pressures also constitute significant institutional challenges. Chen (2014) reported that academic staff often perceive insufficient time to redesign course materials and develop technology-supported learning activities, which limits their willingness to adopt BL. Similarly, Antwi-Boampong (2018) identified barriers such as limited information and communication technology (ICT) capacity, inadequate technical infrastructure, fragmented institutional policies, and insufficient professional development support as factors that constrain faculty adoption of BL. These challenges are largely structural in nature and are typically beyond the direct control of individual academic staff.

2.7.1 Individual Barriers

In addition to institutional constraints, individual-related barriers play a crucial role in shaping academic staff's adoption of BL. Attitudes towards technology, confidence in ICT-related skills, and understanding of e-learning concepts have been consistently identified as key factors influencing these areas (Fazio, 2007; Porter et al., 2016). Misconceptions about e-learning, such as equating it solely with internet use or content sharing, can result in resistance to or avoidance of BL approaches.

Studies have also highlighted personal workload concerns, limited motivation, and anxiety related to online interaction as deterrents to BL adoption (Humbert, 2007; Oh & Park, 2009). Although some earlier studies reflect technological conditions of their time, more recent research continues to report resistance to technology-related change as a persistent barrier, particularly among academic staff who are accustomed to traditional teaching practices (Kisanga & Ireson, 2015; Pynoo et al., 2012). This resistance is often linked to a fear of technological inadequacy, a lack of confidence, and concerns over exposing limited ICT competence.

Demographic and experiential factors have also been discussed in the literature. Differences in age, teaching experience, and prior exposure to technology may influence how academic staff perceive and respond to BL initiatives (Jones & Shao, 2011; Buabeng-Andoh, 2012). These individual variations suggest that technology adoption is not uniform and may require differentiated support strategies.

2.7.2 Knowledge-Related Barriers and Acceptance Issues

A recurring theme across BL adoption studies is the role of technological knowledge. Several studies have reported that limited technological knowledge constrains academic staff's ability to design, adapt, and implement BL effectively (Haron et al., 2012; Kisanga & Ireson, 2015; Mtebe & Raisamo, 2014). Difficulties in converting instructional materials into digital formats and managing online learning systems and activities have been identified as barriers that affect both acceptance and continued use of BL.

Research conducted in Malaysian higher education contexts similarly indicates that although academic staff may hold positive beliefs about the potential of ICT to enhance learning, this does not always translate into consistent technology-supported practice (Hamzah et al., 2010; Sailin, 2014; Abdullah et al., 2019). This intention–practice gap highlights the importance of examining not only attitudes towards BL but also academic staff knowledge readiness and confidence in technology integration.

2.7.3 Implications for Blended Learning Adoption

Overall, the literature suggests that barriers to BL adoption are multifaceted and interconnected, encompassing institutional conditions, individual acceptance, and knowledge-related factors. While technological infrastructure and policy support are necessary, they are insufficient on their own to ensure the successful implementation of BL. Understanding how academic staff perceive, accept, and develop the knowledge required for BL is therefore critical.

These findings underscore the relevance of technology acceptance and knowledge-based frameworks in examining the adoption of BL. By focusing on academic staff technology acceptance and knowledge readiness, this study aims to address gaps in existing research and contribute to a more comprehensive understanding of BL adoption in Malaysian higher education institutions.

2.8 Theoretical framework

This study is grounded in the perspectives of technology adoption and knowledge readiness to examine the factors influencing academic staff adoption of BL in higher education. While early technology acceptance models such as the Technology Acceptance Model (TAM) have been widely used in educational research, these models primarily focus on behavioural intention and system use, with limited attention to the professional knowledge required for effective technology integration in teaching contexts. As a result, the role of academic staff knowledge in shaping technology adoption decisions remains insufficiently addressed within traditional acceptance models.

The primary theoretical framework employed in this study is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh et al. (2012). UTAUT2 extends earlier acceptance models by incorporating both instrumental and experiential determinants of technology use and has demonstrated strong explanatory power for behavioural intention and actual technology use. Compared to TAM, UTAUT2 provides a more comprehensive explanation of technology acceptance, accounting for up to 74% of the variance in behavioural intention and 52% in use behaviour (Venkatesh et al., 2012). Its robustness has been further supported by comparative studies showing superior predictive performance in technology-mediated learning contexts (Hsiao & Tang, 2014; Rondan-Cataluña et al., 2015).

Despite its strengths, UTAUT2 primarily conceptualises technology adoption from a behavioural perspective and does not explicitly account for the professional knowledge that academic staff require to integrate technology meaningfully into teaching. In educational contexts, particularly in the implementation of BL, technology acceptance alone may be insufficient to explain adoption outcomes without considering academic staff's knowledge readiness. This limitation has been highlighted in prior studies, which suggest that the applicability of UTAUT2 in educational settings warrants further empirical validation (Alshahrani & Walker, 2018).

To address this limitation, the present study integrates selected knowledge components from the TPACK framework. TPACK conceptualises the types of knowledge educators require for technology integration in teaching. However, rather than operationalising the full TPACK framework, this study focuses on its core knowledge domains: Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). These components represent foundational knowledge readiness and are appropriate for large-scale, survey-based investigations. The intersecting knowledge domains (TCK, PCK, and TPACK), which reflect enacted instructional design and classroom practice, were not included, as they are more suitably examined through observational or design-based methodologies rather than self-reported data.

Accordingly, TK, PK, and CK were incorporated as additional explanatory variables to complement the UTAUT2 constructs. This integration enables the study to examine BL adoption from both acceptance-driven and knowledge-driven perspectives. As illustrated in the research framework presented in Chapter 1 (Figure 1.1), UTAUT2 constructs function as predictors of behavioural intention and use behaviour, while the TPACK core components represent academic staff's knowledge readiness to adopt BL.

The conceptual framework positions performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, technological knowledge, pedagogical knowledge, and content knowledge as independent variables influencing behavioural intention and actual use of BL. Behavioural intention and use behaviour are treated as dependent variables. Hypotheses were formulated based on this integrated framework and are supported by empirical findings discussed in Chapter 2.

Furthermore, while demographic variables such as age, gender, and teaching experience are theoretically embedded as moderators within UTAUT2, this study does not re-examine their moderating effects on acceptance constructs. Instead, demographic variables are applied exclusively to the TPACK knowledge components to examine variations in academic staff's knowledge readiness for the adoption of BL. This approach addresses an underexplored area in the TPACK literature, which has largely focused on knowledge structure rather than demographic variability.

In summary, UTAUT2 serves as the primary theoretical framework for explaining academic staff's technology acceptance, while selected TPACK core components extend the model by accounting for knowledge readiness. This integrated framework provides a theoretically grounded and contextually appropriate lens for examining BL adoption among academic staff in Malaysian higher education institutions.

Additionally, empirical research on the application of the UTAUT2 model in educational contexts for academic staff in HEIs remains limited (Raman & Don, 2013), particularly in developing countries such as Malaysia, with regard to the implementation of BL (Sharififard et al., 2016), particularly in developing countries such as Malaysia, regarding the implementation of BL (Sharififard et al., 2016). Hence, this study applies the UTAUT2 model as its main theoretical framework to extend empirical understanding of BL adoption among academic staff in Malaysian higher education.

2.8.1 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) to explain user behaviour related to technology adoption within organisational settings. Rather than extending a single acceptance model, UTAUT was formulated by systematically comparing and synthesising eight prominent technology acceptance theories, including the Technology Acceptance Model 2 (TAM2), with the aim of creating a unified framework that incorporates the strengths of each.

TAM2, which extends the original Technology Acceptance Model by incorporating social influence and cognitive instrumental processes, represents one of the key antecedent models informing the development of UTAUT (Venkatesh & Davis, 2000). The structure of TAM2 and its core constructs are illustrated in Figure 2.5, providing important theoretical grounding for later integrative models.

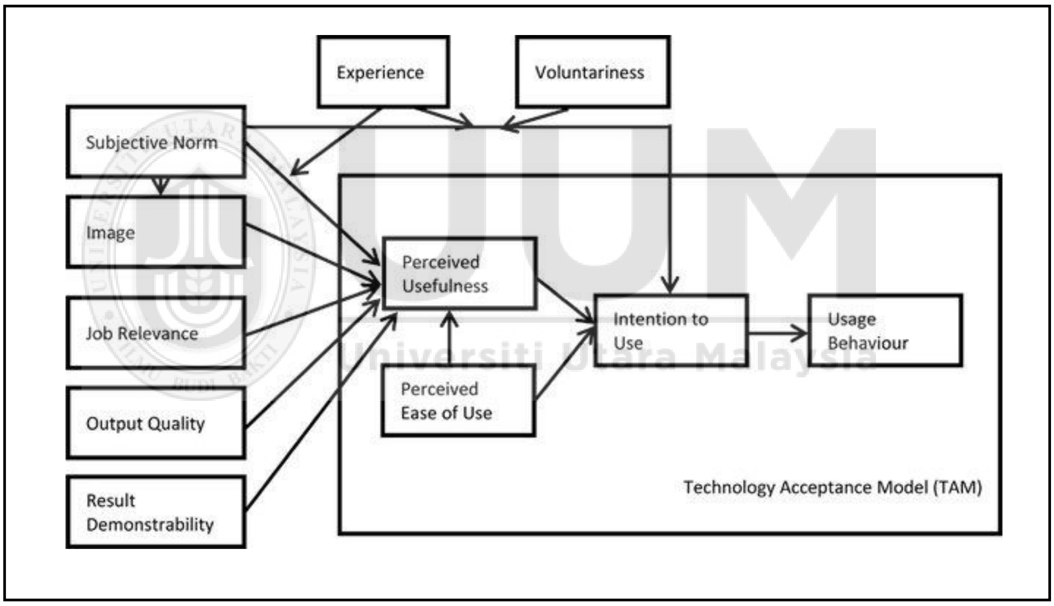

Figure 2.5 Technology Acceptance Model (TAM2)
Source: Venkatesh et al. (2013).

The eight foundational theories integrated into UTAUT are as follows:

- The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975)
- The Theory of Planned Behaviour (TPB) (Ajzen, 1991)
- The Technology Acceptance Model (TAM) (Davis, 1989)
- The Motivational Model (MM) (Davis, Bagozzi, & Warshaw, 1992)
- The Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995)

- The Model of PC Utilisation (MPCU) (Thompson, Higgins, & Howell, 1991)
- Innovation Diffusion Theory (IDT) (Rogers, 1962)
- Social Cognitive Theory (SCT) (Bandura, 1986)

From these theories, UTAUT identifies four core determinants of behavioural intention and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition, the model incorporates four moderating variables, gender, age, experience, and voluntariness of use, to account for differences in technology adoption across user groups. The overall structure of the UTAUT model, along with the relationships among its constructs, is presented in Figure 2.6.

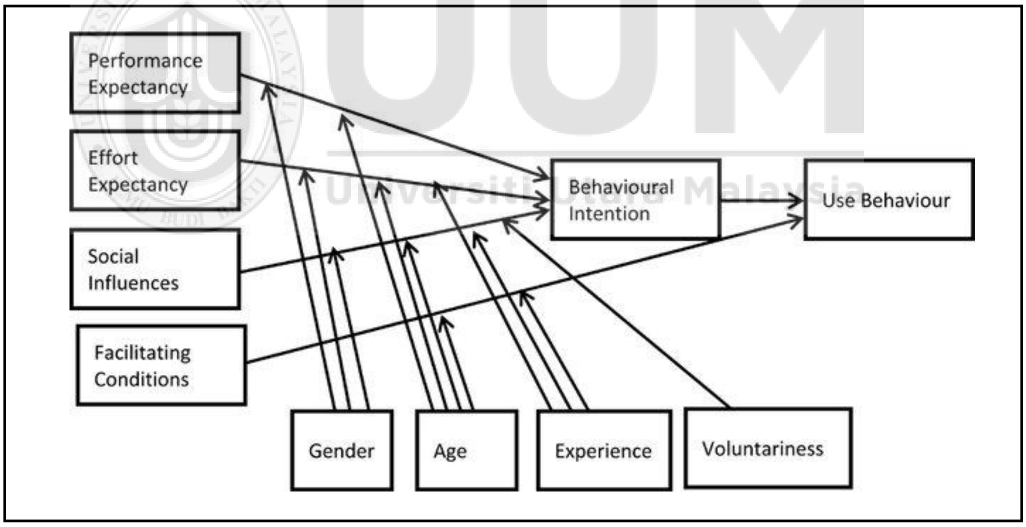

Figure 2.6 Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh et al. (2013).

UTAUT provides a comprehensive and empirically validated framework for explaining technology acceptance across organisational contexts, including education. By integrating key constructs from multiple acceptance theories, the model offers stronger explanatory power than individual models and has been widely adopted in studies examining educators' technology acceptance (Lewis et al., 2013).

2.8.1.0 Performance Expectancy (PE)

Performance expectancy refers to the degree to which an individual believes that using a technology will enhance job performance (Venkatesh et al., 2003). Within the UTAUT framework, PE is conceptually derived from perceived usefulness, extrinsic motivation, job-technology fit, relative advantage, and outcome expectations. In the context of BL, performance expectancy reflects academic staff's beliefs that adopting BL can enhance teaching effectiveness, improve instructional efficiency, and support student learning outcomes. Prior studies have consistently shown that when educators perceive clear performance-related benefits, they are more likely to form positive intentions to adopt educational technologies.

2.8.1.1 Effort Expectancy (EE)

Effort expectancy refers to the degree of ease associated with the use of a technology (Venkatesh et al., 2003). This construct is conceptually aligned with perceived ease of use in earlier acceptance models. In educational settings, effort expectancy captures academic staff's perceptions of how easy it is to learn, implement, and manage BL-related technologies. As users gain experience, perceived effort typically decreases, strengthening their behavioural intention to continue using technology. Accordingly, EE is expected to influence academic staff's behavioural intention to adopt BL, particularly during the early stages of implementation.

2.8.1.2 Social Influence (SI)

Social influence is defined as the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). In organisational settings, this influence may stem from institutional leadership, colleagues, or professional norms. In the context of BL, academic staff's adoption decisions may be shaped by expectations from department heads, faculty management, or institutional policies encouraging technology-enhanced teaching. Prior studies suggest that social influence is particularly salient in environments where technology adoption is institutionally encouraged rather than purely voluntary.

2.8.1.3 Facilitating Conditions (FC)

Facilitating conditions refer to an individual's belief that an organisational and technical infrastructure exist to support the use of a technology (Venkatesh et al., 2003). This includes access to technical support, training opportunities, and compatible systems. In higher education, facilitating conditions reflect the extent to which institutions provide academic staff with adequate technological resources, instructional support, and administrative backing for the implementation of BL. Empirical evidence suggests that strong facilitating conditions can directly influence actual technology use, particularly when institutional support structures are well-established.

2.8.2 Moderators of The Unified Theory of Acceptance and Use of Technology (UTAUT)

The original UTAUT model proposes four moderating variables: age, gender, experience, and voluntariness of use, which influence the relationships between the core constructs and behavioural intention or use behaviour (Venkatesh et al., 2003). These moderators were introduced to account for individual differences in technology adoption behaviour across organisational contexts.

2.8.2.0 Age

Age has been identified as a significant moderator within the UTAUT framework, influencing the strength of the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention (Venkatesh et al., 2003). Empirical findings suggest that the effect of performance expectancy on behavioural intention tends to be stronger among younger users, while effort expectancy and facilitating conditions may have a greater influence on older users. Prior research suggests that incorporating age as a moderator enhances the explanatory power of technology acceptance models (Chung et al., 2010).

2.8.2.1 Gender

Gender differences in technology adoption behaviour have been widely reported in acceptance research. Venkatesh et al. (2003) demonstrated that gender moderates several UTAUT relationships, with performance expectancy exerting a stronger influence on behavioural intention among men, while effort expectancy and social influence tend to be more salient for women. These differences have been attributed to socially constructed cognitive and behavioural orientations toward technology use. The inclusion of gender as a moderator has been shown to improve the predictive power of acceptance models, particularly in organisational technology adoption contexts.

2.8.2.2 Experience

Experience refers to the extent of an individual's prior exposure to and familiarity with a technology. In UTAUT, experience moderates the effects of effort expectancy, social influence, and facilitating conditions on behavioural intention and use behaviour

(Venkatesh et al., 2003). Research suggests that users with limited experience are more influenced by perceived ease of use and social expectations, whereas facilitating conditions become more critical as users gain experience (Castañeda et al., 2007).

2.8.2.3 Voluntariness

Voluntariness of use reflects the degree to which technology adoption is perceived as mandatory or voluntary within an organisation (Venkatesh & Morris, 2000). In the original UTAUT model, voluntariness moderates the effects of performance expectancy, effort expectancy, and social influence on behavioural intention, particularly in mandatory usage settings.

However, voluntariness of use was not included as a moderating variable in this study. This decision was based on the nature of BL adoption in higher education, where academic staff retain a high degree of autonomy in deciding how and whether to integrate technology into their teaching practices. Although institutional policies may encourage the adoption of BL, actual use decisions remain largely voluntary rather than system-mandated. Consistent with prior educational technology studies, voluntariness was therefore excluded to maintain conceptual relevance and avoid redundancy in the analytical model.

Furthermore, while age, gender, and experience are theoretically embedded as moderators within the UTAUT framework, this study does not re-examine their moderating effects on UTAUT constructs. Instead, these demographic variables are applied specifically to the TPACK knowledge components to investigate variation in academic staff's knowledge readiness for BL adoption. This approach allows the study to extend existing literature by examining demographic influences on professional knowledge domains rather than replicating established moderation effects within UTAUT.

2.8.3 The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The Unified Theory of Acceptance and Use of Technology was extended by Venkatesh et al. (2012) to form UTAUT2, incorporating additional constructs to better explain technology adoption in consumer-oriented contexts. UTAUT2 introduces three new determinants: Hedonic Motivation (HM), Price Value (PV) and Habit (HT), to capture experiential and behavioural factors that were not explicitly addressed in the original UTAUT model. Figure 2.7 illustrates the UTAUT2 framework and its additional constructs.

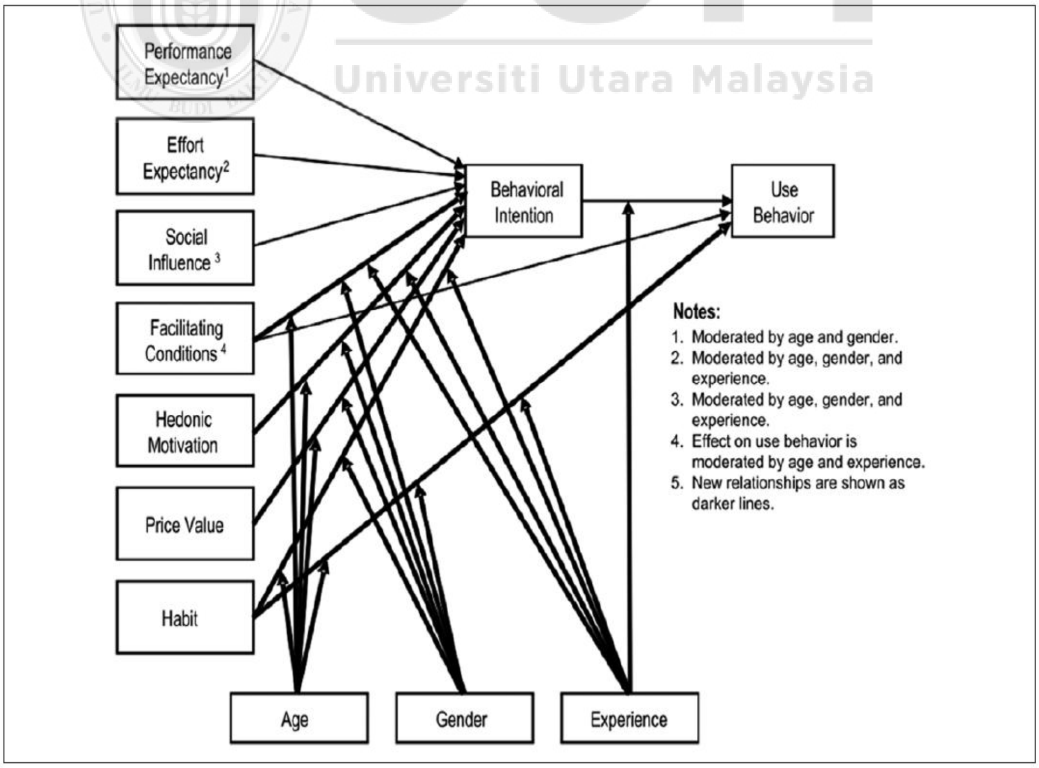

Figure 2.7 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)
Source: (Venkatesh et al., 2013).

Although UTAUT2 was initially developed for consumer technology use, subsequent studies have demonstrated its applicability in educational and organisational settings, particularly in explaining voluntary and experience-based technology adoption. In the context of BL adoption among academic staff, selected UTAUT2 constructs were incorporated based on their theoretical relevance and contextual appropriateness.

2.8.3.0 Hedonic Motivation (HM)

Hedonic motivation refers to the degree of pleasure, enjoyment, or intrinsic satisfaction derived from using a technology (Brown & Venkatesh, 2005; Venkatesh et al., 2012). Rooted in intrinsic motivation theory, HM captures affective responses to technology use that extend beyond functional performance outcomes. In UTAUT2, hedonic motivation has been shown to exert a strong influence on behavioural intention, particularly in voluntary usage contexts.

In educational settings, hedonic motivation reflects academic staff's enjoyment and positive affect associated with using BL tools and platforms. When academic staff perceive BL technologies as engaging or enjoyable, they are more likely to develop favourable intentions toward continued use. Accordingly, HM was included in this study as a relevant predictor of behavioural intention to adopt BL.

2.8.3.1 Price Value (PV)

Price value refers to users' cognitive trade-off between the perceived benefits of a technology and the monetary cost associated with its use (Dodds et al., 1991; Venkatesh et al., 2012). In consumer contexts, PV has been shown to influence adoption decisions when users directly bear financial costs.

However, price value was excluded from this study due to its limited relevance in the institutional context of public higher education. In Malaysian public universities, academic staff typically have access to BL technologies, internet connectivity, and institutional platforms at no personal financial cost. Consequently, monetary considerations are unlikely to play a significant role in shaping academic staff's behavioural intention to adopt BL. Moreover, prior studies employing PV have primarily focused on consumer technologies such as e-commerce, mobile payment systems, and online banking (Arenas-Gaitán et al., 2015; Morosan & DeFranco, 2016; Pappas, 2017). Including PV in the present study would therefore offer limited explanatory value and risk conceptual misalignment. For these reasons, PV was deliberately excluded from the research model.

2.8.3.2 Habit (HT)

Habit refers to the extent to which individuals tend to perform behaviours automatically as a result of learning and repeated experience (Limayem et al., 2007; Kim & Malhotra, 2005). In UTAUT2, habit represents behavioural automation that develops over time and has been shown to influence both behavioural intention and actual technology use (Venkatesh et al., 2012).

In the context of BL adoption, habit reflects academic staff's routine use of digital tools and technology-supported teaching practices developed through prior exposure and institutional initiatives. As BL implementation often builds on existing teaching habits and prior technology use, habit is considered a theoretically relevant and contextually appropriate predictor of both intention and use behaviour. Accordingly, HT was retained in the study to capture the role of prior experience and behavioural routinisation in academic staff's adoption of BL.

2.8.4 Past Research

Venkatesh et al. (2012) categorised extensions of the UTAUT framework into three broad approaches: (i) application of UTAUT2 in contexts beyond consumer settings, including organisational and educational environments; (ii) integration of additional constructs such as trust, self-efficacy, or institutional variables; and (iii) inclusion of exogenous theoretical frameworks to enrich explanatory power. These extensions reflect ongoing scholarly efforts to adapt technology acceptance models to diverse contexts and evolving research needs.

Early applications of UTAUT and UTAUT2 predominantly focused on consumer and business-related technologies, including online banking, e-commerce, mobile internet services, and social networking platforms (Alwahaishi & Snášel, 2013; Cheng et al., 2011; Chong, 2013; Eckhardt et al., 2009; Zhou et al., 2010). These studies consistently validated the robustness of UTAUT-based models in predicting behavioural intention and technology use, thereby establishing a strong empirical foundation for subsequent adaptations in non-commercial settings.

Following the introduction of UTAUT2, research increasingly explored its applicability in educational contexts, particularly in relation to students' adoption of e-learning, mobile learning, and LMS. For instance, Bharati and Srikanth (2018) extended UTAUT2 by incorporating quality of service and interactive visual information to examine mobile learning adoption among university students. Similarly, Tarhini et al. (2017) integrated trust and self-efficacy into the UTAUT2 model, demonstrating their influence on students' acceptance of e-learning technologies. These studies indicate that UTAUT2 has been primarily employed to examine student perspectives, often through the inclusion of context-specific constructs.

In the Malaysian context, UTAUT has been applied to examine technology acceptance across various educational technologies, including virtual learning environments, social media platforms, and mobile learning systems (Hamdan et al., 2015; Raman & Lateh, 2015; Shakila et al., 2018; Tey & Moses, 2018). However, empirical studies employing the UTAUT2 model within Malaysian higher education remain relatively limited, particularly those focusing on academic staff. One notable exception is the study by Raman and Don (2013), which examined preservice lecturers' acceptance of LMS using the UTAUT2 model. While informative, the study did not extend the model with additional constructs to account for the professional knowledge demands specific to academic staff in teaching contexts.

Empirical findings across UTAUT2-based educational studies have also revealed inconsistent results regarding the significance of individual constructs. For example, Dakduk et al. (2018) reported that performance expectancy, effort expectancy, and hedonic motivation significantly influenced lecturers' behavioural intention to adopt BL, while social influence and habit were not significant. Conversely, Khan and Adams (2016) found that performance expectancy, effort expectancy, social influence, and hedonic motivation predicted faculty adoption of LMS, whereas habit was not a significant predictor. Other studies reported varying combinations of significant predictors, including habit, facilitating conditions, and trust (Frank & Milković, 2018; Raman & Don, 2013; Tarhini et al., 2017). These mixed findings suggest that the explanatory power of UTAUT2 constructs may be context-dependent and influenced by institutional, cultural, and professional factors.

Importantly, existing UTAUT2-based studies in education have largely focused on behavioural intention and system usage without explicitly accounting for academic staff's professional knowledge. Technology acceptance models, including UTAUT2, do not include constructs that capture educators' technological, pedagogical, or content-related knowledge, despite these being central to effective technology integration in teaching (Batiibwe & Bakkabulindi, 2016). Prior research has highlighted that academic staff's cognitive and knowledge-related factors significantly influence decision-making and technology-related behaviour in instructional settings (Kramarski & Michalsky, 2010; Shin, 2013).

To address this limitation, scholars have increasingly advocated for the integration of complementary theoretical frameworks when studying technology adoption in education. Previous studies have combined TAM with the Community of Inquiry framework (Ateş Çobanoğlu, 2018), TAM with the Theory of Planned Behaviour (Johanne et al., 2015), and UTAUT with the Community of Inquiry framework (Radovan & Kristl, 2017) to better capture pedagogical and contextual dimensions of BL. These integrative approaches demonstrate that single-model explanations may be insufficient to account for the complexity of educational technology adoption.

Furthermore, demographic variables such as age, gender, and experience have been widely examined as moderators within UTAUT and UTAUT2. While some studies report significant moderating effects (Chung et al., 2010; Tarhini et al., 2014), others report weak or non-significant relationships (Altawallbeh et al., 2015; Kao et al., 2018). Despite these inconsistencies, the moderating role of demographic variables within UTAUT-based models has been extensively explored, resulting in diminishing theoretical returns from further replication.

In contrast, the moderating effects of demographic variables on academic staff's professional knowledge, particularly in terms of technological, pedagogical, and content knowledge, remain relatively underexplored. The TPACK framework conceptualises these knowledge domains as critical for technology integration in teaching (Mishra & Koehler, 2006), yet existing studies have predominantly examined their direct effects rather than variations across demographic groups. Examining how age, gender, and teaching experience influence knowledge readiness, therefore, offers a meaningful extension beyond established acceptance-based moderation analyses.

Accordingly, this study integrates six UTAUT2 constructs to explain academic staff's behavioural intention to adopt BL, while incorporating three core TPACK components: technological knowledge, pedagogical knowledge, and content knowledge, to capture professional knowledge readiness. Demographic variables are applied exclusively as moderators to the TPACK components, rather than to UTAUT2 constructs, to address a clearly identified gap in the literature. This integrated approach directly addresses the limitations of prior research and provides a more contextually grounded understanding of BL adoption among academic staff in Malaysian higher education.

2.8.5 Technological Pedagogical and Content Knowledge

Rapid advancements in educational technologies have introduced increasing complexity into teaching environments, requiring academic staff to rely on their professional knowledge to integrate technology meaningfully into instruction. While technology offers significant pedagogical potential, its effective use depends on academic staff's understanding of how technology relates to their teaching knowledge and subject content. Previous research has noted that technology often remains a "black box" for educators when knowledge readiness is insufficient, resulting in reluctance or superficial use of digital tools (Mueller & Wood, 2012).

To conceptualise educators' professional knowledge in technology-enhanced teaching, Mishra and Koehler (2006) extended Shulman's Pedagogical Content Knowledge (PCK) framework by introducing the Technological Pedagogical and Content Knowledge (TPACK) model. TPACK identifies the knowledge domains educators require to integrate technology into teaching, encompassing technological knowledge, pedagogical knowledge, and content knowledge. While the full TPACK framework includes intersecting knowledge domains (e.g., TCK, PCK, and TPACK), this study focuses specifically on the core knowledge components, technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK) as indicators of academic staff's knowledge readiness for adopting BL.

This selective focus is intentional and methodologically grounded. The intersecting TPACK components represent enacted instructional design and classroom integration, which are more appropriately examined through classroom observation, artefact analysis, or design-based research. In contrast, the core components of TPACK reflect foundational knowledge domains that can be reliably examined using self-reported survey instruments. Accordingly, TK, PK, and CK were selected to align with the study's quantitative, cross-sectional design and its emphasis on readiness rather than instructional performance.

2.8.5.0 Technological Knowledge (TK)

Technological knowledge refers to academic staff's understanding of digital tools, systems, and technologies relevant to teaching and learning (Mishra & Koehler, 2006). This includes knowledge of both basic instructional technologies and more advanced digital applications, such as LMS, multimedia tools, and online communication platforms. Prior research suggests that insufficient technological knowledge can limit educators' confidence and willingness to adopt technology-enhanced teaching practices (Garrett, 2014; Yalley, 2017). Variability in technological environments and inconsistent exposure to training further contribute to disparities in TK, influencing educators' readiness to integrate BL effectively.

2.8.5.1 Pedagogical Knowledge (PK)

Pedagogical knowledge refers to academic staff's understanding of teaching strategies, instructional methods, assessment approaches, and ways of facilitating student learning (Shulman, 1987; Mishra & Koehler, 2006). In this study, PK is conceptualised as a knowledge foundation, rather than as enacted pedagogy. It reflects academic staff's perceived capability to plan, adapt, and evaluate teaching approaches in technology-supported environments. Prior studies indicate that educators' pedagogical understanding influences their perceptions of system usefulness and acceptance of learning technologies (Bratt, 2009; McFarland & Hamilton, 2006). As such, PK is considered a relevant knowledge readiness factor in BL adoption.

2.8.5.2 Content Knowledge (CK)

Content knowledge refers to academic staff's mastery of subject matter, including concepts, theories, and disciplinary frameworks relevant to their teaching fields

(Mishra & Koehler, 2006). Strong CK has been consistently associated with effective instructional decision-making and confidence in technology integration (Bain, 2004). However, the availability of digital content alone does not guarantee its use in teaching. Studies have shown that limited content knowledge can hinder educators' ability to leverage technology meaningfully, even when institutional systems and resources are available (Mtebe et al., 2016). Therefore, CK is included as a foundational knowledge component influencing academic staff's readiness to adopt BL.

In summary, the TPACK framework offers a theoretically grounded approach to capturing academic staff's professional knowledge in technology-enhanced teaching contexts. This study adopts the core TPACK components: TK, PK, and CK, to represent knowledge readiness, rather than instructional enactment. These components are integrated with selected UTAUT2 constructs to examine how acceptance-related and knowledge-related factors jointly influence academic staff's intention to adopt and use BL. This integration aligns with the study's objectives and addresses identified gaps in existing research on technology adoption in higher education.

2.9 Research Hypotheses

This study examines the relationships between factors influencing academic staff's adoption of BL. The UTAUT2 framework (Venkatesh et al., 2012), as illustrated in Figure 2.8, underpins the examination of behavioural intention by specifying key technology acceptance determinants. Based on this framework, the following hypotheses were formulated to test the direct effects of selected UTAUT2 constructs on academic staff's behavioural intention (BI) to adopt BL.

2.9.1 Hypotheses for UTAUT2 Variables

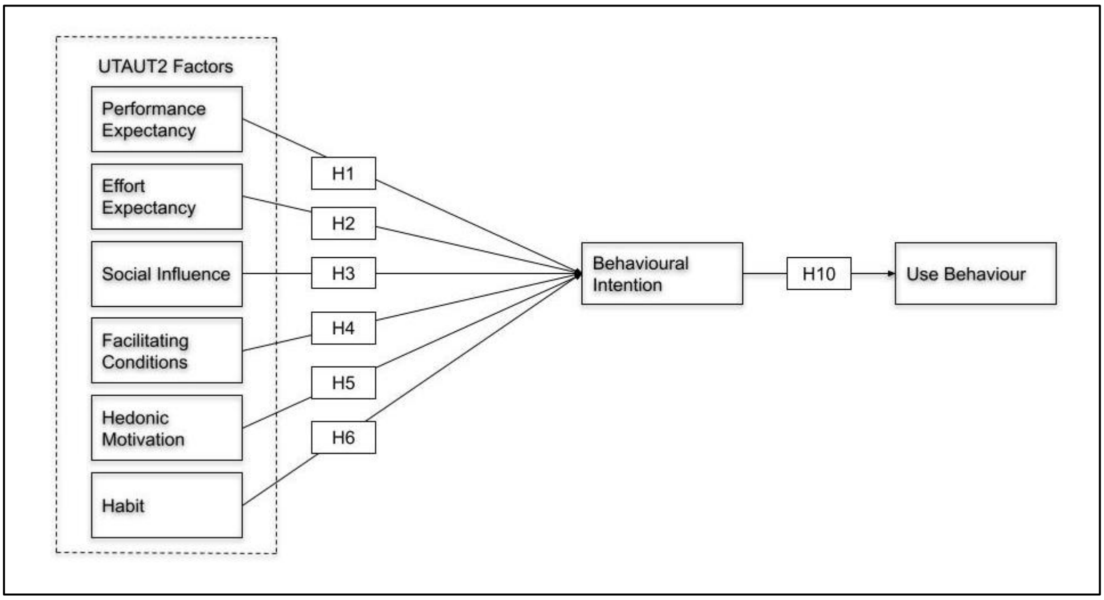

Figure 2.8 UTAUT2 Factors

Figure 2.8 illustrates the conceptual framework examining the influence of six UTAUT2 constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Habit (HT), on academic staff's behavioural intention to adopt BL. The hypotheses (H1–H6) are derived from prior technology acceptance research and BL literature.

Performance Expectancy (PE)

Performance Expectancy refers to the degree to which an individual believes that using a particular technology will enhance job performance (Venkatesh et al., 2003). In BL contexts, PE reflects academic staff's beliefs that BL can improve instructional effectiveness, student engagement, assessment efficiency, and overall teaching outcomes.

Numerous studies have established PE as a strong predictor of behavioural intention in educational technology adoption (Abushanab & Pearson, 2007; Deng et al., 2011;

Eckhardt et al., 2009). Within Malaysian higher education, PE has consistently demonstrated a significant influence on behavioural intention to adopt learning technologies (Hamdan et al., 2015; Raman & Rathakrishnan, 2018; Shakila et al., 2018).

Importantly, BL-specific studies have confirmed that academic staff are more likely to adopt BL when they perceive clear instructional benefits, such as flexibility, improved learning outcomes, and enhanced interaction (Martin-Garcia & Sanchez-Gomez, 2014; Dziuban et al., 2018; Porter et al., 2016). Accordingly, the following hypothesis is proposed:

H1: Performance Expectancy has a significant influence on academic staff's behavioural intention to adopt BL.

Effort Expectancy (EE)

Effort Expectancy refers to the degree of ease associated with the use of a system (Venkatesh et al., 2003). In BL environments, EE reflects academic staff's perceptions of how easy it is to design, manage, and deliver blended courses using digital platforms.

Previous studies in Malaysia have found that EE significantly influences behavioural intention to adopt educational technologies (Hamdan et al., 2015; Khairah@Asma'a et al., 2017; Raman & Lateh, 2015). BL-focused studies further indicate that when BL systems are perceived as user-friendly and require minimal technical effort, academic staff are more willing to integrate them into their teaching practice (Alammary et al., 2014; Martin-Garcia & Sanchez-Gomez, 2014). Thus, the following hypothesis is proposed:

H2: Effort Expectancy has a significant influence on academic staff's behavioural intention to adopt BL.

Social Influence (SI)

Social Influence refers to the extent to which individuals perceive that important others believe they should use a particular system (Venkatesh et al., 2003). In higher education settings, SI may originate from institutional leadership, colleagues, faculty culture, or national policy expectations.

Several Malaysian studies have reported significant positive relationships between SI and behavioural intention to use educational technologies (Chan & Sya Azmeela Shariff, 2016; Hamdan et al., 2015; Raman & Rathakrishnan, 2018). In BL contexts, academic staff's adoption decisions are often shaped by departmental norms, peer practices, and institutional encouragement (Martin-Garcia & Sanchez-Gomez, 2014; Porter & Graham, 2016). Accordingly, the following hypothesis is proposed:

H3: Social Influence has a significant influence on academic staff's behavioural intention to adopt BL.

Facilitating Conditions (FC)

Facilitating Conditions refer to individuals' perceptions of the availability of organisational and technical support to enable system use (Venkatesh et al., 2003). In BL contexts, facilitating conditions include access to learning management systems (LMS), technical support, training opportunities, instructional design assistance, and institutional infrastructure.

BL-specific studies have demonstrated that insufficient technical support, inadequate infrastructure, and lack of professional development remain major barriers to BL adoption among academic staff, particularly when managing both online and face-to-face instructional components (Porter et al., 2016; Moskal et al., 2013; Dziuban et al., 2018). Empirical evidence from BL research further indicates that strong facilitating conditions significantly enhance academic staff's intention to adopt and sustain BL practices (Salloum & Shaalan, 2018; El-Masri & Tarhini, 2017; Al-Fraihat et al., 2020).

Within the Malaysian context, institutional readiness and support structures have been shown to directly influence educators' acceptance of blended and online learning approaches (Lim et al., 2019; Seong et al., 2022). In BL environments, facilitating conditions are particularly critical because academic staff must coordinate face-to-face instruction with synchronous and asynchronous online components, which requires sustained institutional support, training, and technical infrastructure. Therefore, this study proposes:

H4: Facilitating Conditions have a significant influence on academic staff's behavioural intention to adopt BL.

Hedonic Motivation (HM)

Hedonic Motivation refers to the degree of pleasure or enjoyment derived from using a technology (Brown & Venkatesh, 2005). In BL environments, HM may arise from positive teaching experiences, creative instructional design, and satisfaction with interactive digital tools.

Prior research has confirmed HM as a significant predictor of behavioural intention in educational technology adoption (El-Masri & Tarhini, 2017; Raman & Don, 2013). BL-related studies further suggest that academic staff are more inclined to adopt BL when the teaching experience is engaging and rewarding (Dakduk et al., 2018; Dziuban et al., 2018). Thus, the following hypothesis is proposed:

H5: Hedonic Motivation has a significant influence on academic staff's behavioural intention to adopt BL.

Habit (HT)

Within BL contexts, habit develops through repeated engagement with digital platforms alongside routine face-to-face teaching activities. Habit refers to the extent to which individuals tend to perform behaviours automatically as a result of learning and repeated experience (Limayem et al., 2007; Venkatesh et al., 2012). In BL environments, habit reflects academic staff's routine use of digital platforms, LMS tools, and online instructional practices.

Recent BL research indicates that sustained exposure to blended and online teaching during and after the COVID-19 pandemic has contributed to the habitual use of digital teaching tools among academic staff (Bond et al., 2021; Rapanta et al., 2020; Khalid et al., 2023). Once blended practices become embedded in routine teaching activities, habit plays a significant role in predicting continued adoption and intention to use BL (Tarhini et al., 2017; Dakduk et al., 2018). Accordingly, this study proposes:

H6: Habit has a significant influence on academic staff's behavioural intention to adopt BL.

2.9.2 Hypotheses for TPACK Variables

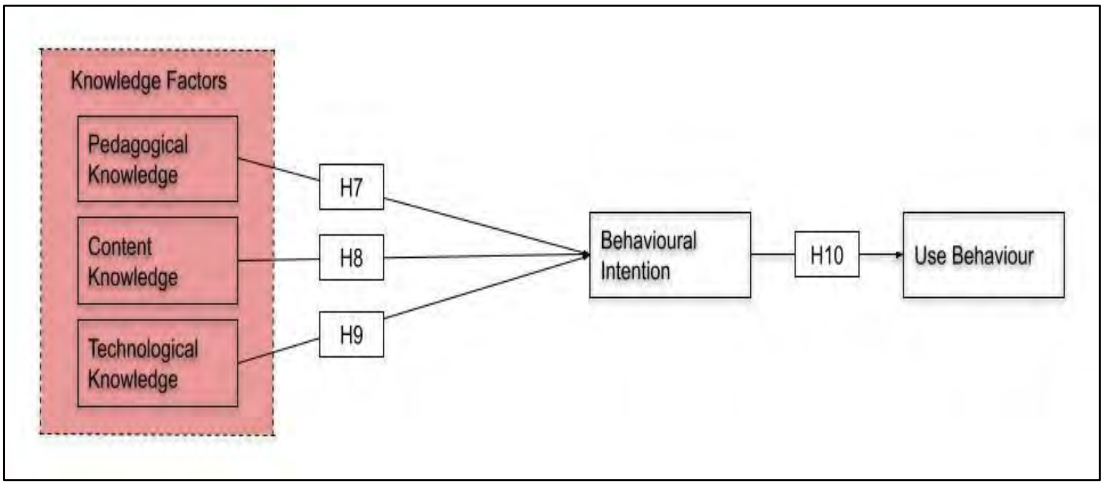

Figure 2.9 Knowledge Factors

Figure 2.9 presents the conceptual framework for examining the direct relationships between the core knowledge components of the TPACK framework: Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK), and academic staff's behavioural intention (BI) to adopt BL. In this framework, BI functions as a proximal determinant of actual use, consistent with established technology acceptance models, thereby linking knowledge readiness to BL implementation.

Drawing on prior studies in technology integration and teacher knowledge, this section outlines the theoretical rationale for the proposed hypotheses (H7 to H9), focusing specifically on how academic staff's core knowledge domains influence their behavioural intention to adopt BL

Pedagogical Knowledge (PK)

Pedagogical Knowledge refers to academic staff's understanding of teaching methods, instructional strategies, assessment practices, and the principles that guide effective learning (Mishra & Koehler, 2006). PK enables instructors to select and adapt teaching approaches that align with students' learning needs and educational objectives.

Skilled academic staff are able to determine which instructional methods best suit different learning contexts and student profiles (Wright, 2009). Prior studies have also indicated that academic staff's pedagogical competence influences their perceptions of the usefulness and effectiveness of learning technologies (Bratt, 2009b). When academic staff possess a wide repertoire of teaching strategies, they are more capable of aligning technology with pedagogy rather than viewing it as an added burden.

In the context of BL, strong PK supports informed decisions about how online and face-to-face components can be combined to enhance learning. Therefore, academic staff with higher levels of PK are more likely to develop positive intentions toward adopting BL.

H7: Pedagogical Knowledge has a significant influence on academic staff's behavioural intention to adopt BL.

Content Knowledge (CK)

Content Knowledge refers to academic staff's depth of understanding of the subject matter they teach, including key concepts, theories, structures, and disciplinary practices (Shulman, 1986). CK reflects mastery of the academic content that forms the foundation of instruction.

Empirical studies have shown that insufficient CK can hinder the effective implementation of e-learning and BL initiatives. For instance, Mtebe, Mbwilo, and Kissaka (2016) found that academic staff with limited subject knowledge experienced difficulties in designing and delivering technology-supported instruction. Strong CK enables academic staff to focus on pedagogical innovation rather than struggling with content delivery.

In BL environments, academic staff with strong CK are better positioned to select appropriate learning activities, resources, and assessments across both online and face-to-face modes. As such, CK is expected to positively influence academic staff's behavioural intention to adopt BL.

H8: Content Knowledge (CK) has a significant influence on academic staff's behavioural intention to adopt BL.

Technological Knowledge (TK)

Technological Knowledge refers to academic staff's understanding of, and ability to operate, technological tools and systems relevant to teaching and learning, including hardware, software applications, and digital platforms (Mishra & Koehler, 2006). TK encompasses both basic operational skills (e.g., word processing, email, and LMS) and more advanced competencies required for integrating technology meaningfully into instruction.

Previous research has shown that a lack of fundamental technological knowledge and computer skills constrains academic staff's ability to utilise ICT effectively (Yalley, 2017). When academic staff lack confidence in their technological capabilities, they are less likely to experiment with or adopt BL approaches. Conversely, adequate TK enables instructors to navigate digital platforms with greater ease and reduces barriers to adoption.

Accordingly, it is expected that academic staff with higher levels of TK will demonstrate stronger behavioural intention to adopt BL.

H9: Technological Knowledge has a significant influence on academic staff's behavioural intention to adopt BL.

Behavioural Intention (BI)

Behavioural Intention refers to an individual's readiness and deliberate effort to perform a specific behaviour (Ajzen, 1991). Within technology acceptance research, BI is consistently identified as a strong and proximal predictor of actual technology use.

Numerous studies have confirmed that intention to use technology translates into actual use behaviour across educational and organisational contexts (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Lewis et al., 2013; Venkatesh et al., 2012). In the context of BL, academic staff are more likely to engage in blended teaching practices when a clear behavioural intention is present.

Accordingly, BI is positioned as a direct antecedent of actual BL use (USE) in this study.

H10: Behavioural Intention (BI) has a significant influence on the actual use of BL (USE).

2.9.3 Hypotheses for Moderating Variables

Prior studies based on the UTAUT and UTAUT2 models have demonstrated that demographic variables such as gender, age, and experience can moderate the relationships between core acceptance constructs and behavioural intention (Venkatesh et al., 2003; Venkatesh et al., 2012). These moderators help explain variations in technology adoption behaviour across different user groups.

2.9.3.0 Moderating Effects in UTAUT2 (Theoretical Context)

Within the UTAUT2 framework, gender, age, and experience have been shown to moderate several relationships between acceptance constructs and behavioural intention:

Facilitating Conditions (FC):

Gender, age, and experience have been shown to moderate the relationship between facilitating conditions and behavioural intention (Venkatesh et al., 2012). Prior studies suggest that women tend to rely more on organisational support and resources when adopting new technologies (Lakhal et al., 2013). The influence of facilitating conditions is also stronger among older individuals, who may experience reduced cognitive flexibility and greater reliance on structured support (Khechine et al., 2014; Martin Garcia & Sanchez Gomez, 2014). In contrast, individuals with greater experience typically develop stronger internal knowledge structures, reducing their dependence on external support (Venkatesh et al., 2012).

Hedonic Motivation (HM):

Gender, age, and experience have also been reported to moderate the relationship between hedonic motivation and behavioural intention (Venkatesh et al., 2012). The effect of hedonic motivation tends to be stronger among younger users and males, who may be more responsive to the enjoyment and novelty associated with technology use (Kasaj & Xhindi, 2016). Findings related to experience remain mixed, with some studies indicating stronger effects among more experienced users (Dakduk et al., 2018), while others report diminishing effects as experience increases (Venkatesh et al., 2012).

Habit (HT):

Habit has likewise been shown to interact with demographic variables. The relationship between habit and behavioural intention is generally stronger among men, who are more likely to rely on established cognitive schemata and routines (Venkatesh et al., 2012). Older individuals often demonstrate more entrenched habits, making behavioural change more challenging when adopting new technologies. Experience also plays a role, as habits are typically formed through prolonged and repeated use.

While these moderating effects are well-documented within UTAUT2, the present study does not empirically test demographic moderators on UTAUT2 constructs, as these relationships have been extensively validated in prior research.

2.9.3.1 Rationale for Moderating TPACK Variables

Instead of applying demographic moderators to the UTAUT2 constructs, this study applies gender, age, and teaching experience as exclusive moderators of the TPACK knowledge components. This decision is theoretically and methodologically justified. The moderating effects of demographic variables on UTAUT2 constructs have been extensively examined and empirically validated across a wide range of contexts, including organisational and educational settings (Venkatesh et al., 2012, 2016). As such, re-examining these established moderation relationships would offer limited incremental theoretical contribution and risk conceptual and empirical redundancy.

In contrast, the moderating influence of demographic characteristics on the professional knowledge domains of academic staff remains comparatively underexplored. Existing TPACK research has predominantly focused on examining direct relationships between knowledge components and instructional outcomes, with limited attention to interaction effects, particularly within BL contexts (Scherer et al., 2017; Scherer & Teo, 2019). This gap suggests a need to move beyond purely linear models and to examine how demographic factors condition the extent to which academic staff's knowledge readiness translates into behavioural intention to adopt BL.

Moreover, academic staff knowledge development is inherently shaped by individual and professional characteristics. Factors such as age, gender, and teaching experience influence exposure to technology, pedagogical training, disciplinary expertise, and confidence in instructional decision-making. Investigating these variables as moderators of TPACK components, therefore, provides insights that are more contextually grounded and analytically meaningful for understanding BL adoption in higher education, compared to re-examining generic acceptance-based relationships.

This study restricts the moderation analysis to the TPACK knowledge components to avoid conceptual and empirical redundancy, while contributing original empirical evidence to the literature. This approach enables a clearer examination of how knowledge readiness varies across demographic groups and how such variation influences academic staff's behavioural intention. In doing so, the study contributes to ongoing efforts to integrate UTAUT2 and TPACK by examining technology acceptance and knowledge readiness as complementary yet analytically distinct dimensions of BL adoption. This positioning responds to recent calls for educational technology adoption models that go beyond behavioural acceptance and explicitly consider educators' knowledge readiness and teaching context (Tamilmani et al., 2020; Scherer & Teo, 2019).

2.9.3.2 Gender as a Moderator

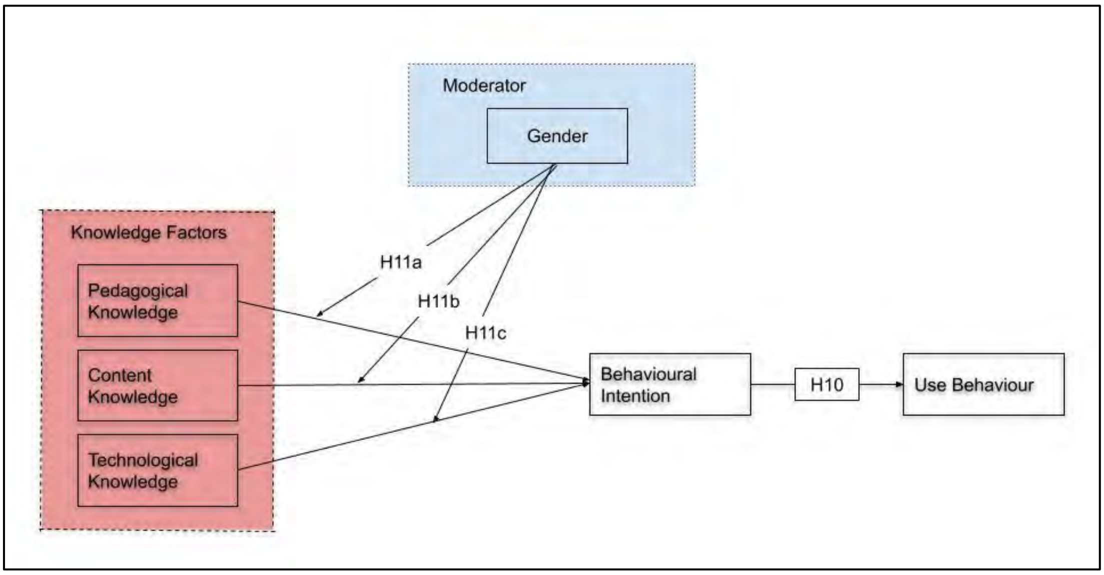

Figure 2.10 Gender as a Moderator

Figure 2.10 illustrates the conceptual framework for examining gender as a moderating variable in the relationships between the core TPACK components: Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), and Behavioural Intention (BI) to adopt BL. Rather than assuming inherent differences in capability, gender is conceptualised as a contextual factor related to social and institutional influences that may affect how different forms of knowledge translate into behavioural intention.

Prior research suggests that gender may shape confidence levels, professional socialisation, and technology-related experiences, which in turn may affect how academic staff leverage their knowledge when adopting technology-enhanced teaching approaches (Venkatesh et al., 2012; Scherer et al., 2017). Accordingly, gender is examined as a moderating variable affecting the strength and direction of the relationships between TPACK components and BI.

Content Knowledge (CK)

Previous studies have reported gender-related differences in self-perceived content expertise, with male academic staff often reporting higher levels of confidence in disciplinary knowledge (Koh et al., 2010). Such differences in self-efficacy perceptions may influence how content knowledge contributes to behavioural intention to adopt BL. However, these findings do not imply differences in actual competence, but rather differences in perception and confidence. Consequently, the following hypothesis is proposed:

H11a: Gender moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

Pedagogical Knowledge (PK)

Research indicates that female academic staff often report stronger pedagogical orientations and a greater emphasis on student-centred teaching practices (Lin et al., 2013). These pedagogical dispositions may influence how pedagogical knowledge translates into behavioural intention to adopt BL, particularly in contexts that require instructional flexibility and learner engagement. Consequently, the following hypothesis is proposed:

H11b: Gender moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

Technological Knowledge (TK)

Empirical studies have reported gender-related differences in technological confidence and experience, with male academic staff often reporting higher perceived technological competence (Cheng & Xie, 2018). Such differences may condition the extent to which technological knowledge translates into behavioural intention to use

BL, especially in institutionally supported environments. Consequently, the following hypothesis is proposed:

H11c: Gender moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

2.9.3.3 Age as a Moderator

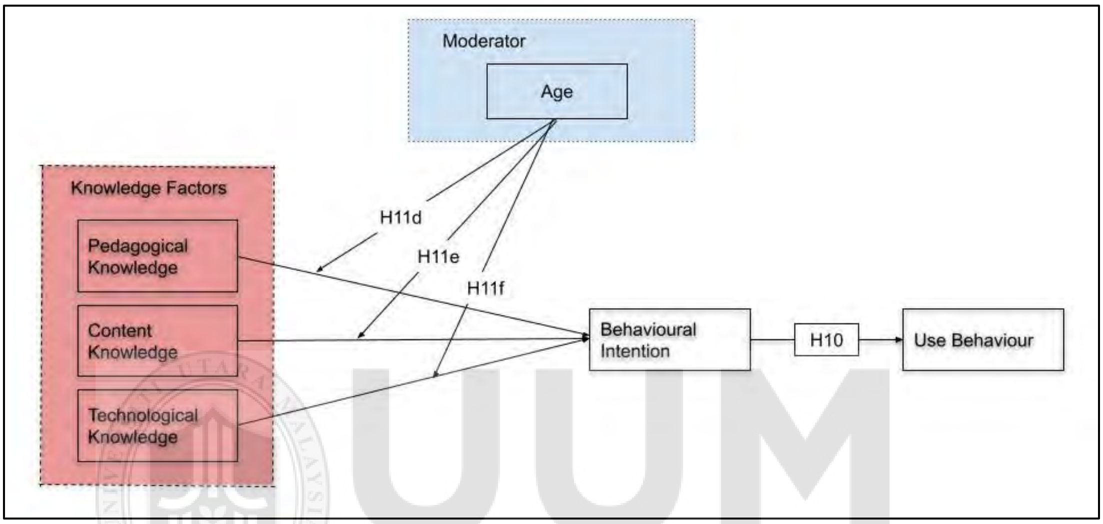

Figure 2.11 Age as a Moderator

Figure 2.11 presents the conceptual framework for examining age as a moderating variable in the relationships between CK, PK, and TK and Behavioural Intention (BI) to adopt BL. Age is conceptualised as a factor reflecting accumulated professional experience, generational exposure to technology, and adaptability to instructional and technological change.

Prior studies have demonstrated that age can influence technology-related beliefs and learning orientations, thereby influencing how knowledge domains relate to BI (Venkatesh et al., 2003; Chung et al., 2010).

Content Knowledge (CK)

Studies have shown that younger academic staff, particularly those in early career stages, may report lower self-perceived content knowledge, partly due to limited teaching experience (Luik et al., 2018). As a result, age may condition how CK contributes to behavioural intention to adopt BL. Consequently, the following hypothesis is proposed:

H11d: Age moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

Pedagogical Knowledge (PK)

While some studies report a negative statistical association between age and PK among pre-service academic staff (Luik et al., 2018), more experienced academic staff often report more refined pedagogical understanding developed through years of classroom practice. These contrasting patterns suggest that age may influence how PK translates into behavioural intention to adopt BL. Consequently, the following hypothesis is proposed:

H11e: Age moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

Technological Knowledge (TK)

Empirical evidence regarding the relationship between age and technological knowledge is mixed and context-dependent. While some studies report no significant association (Cheng & Xie, 2018), others indicate that younger academic staff tend to report higher technological familiarity and confidence (Liang et al., 2013). Consequently, age may moderate the strength of the relationship between TK and BI in the adoption of BL.

H11f: Age moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

2.9.3.4 Teaching Experience as a Moderator

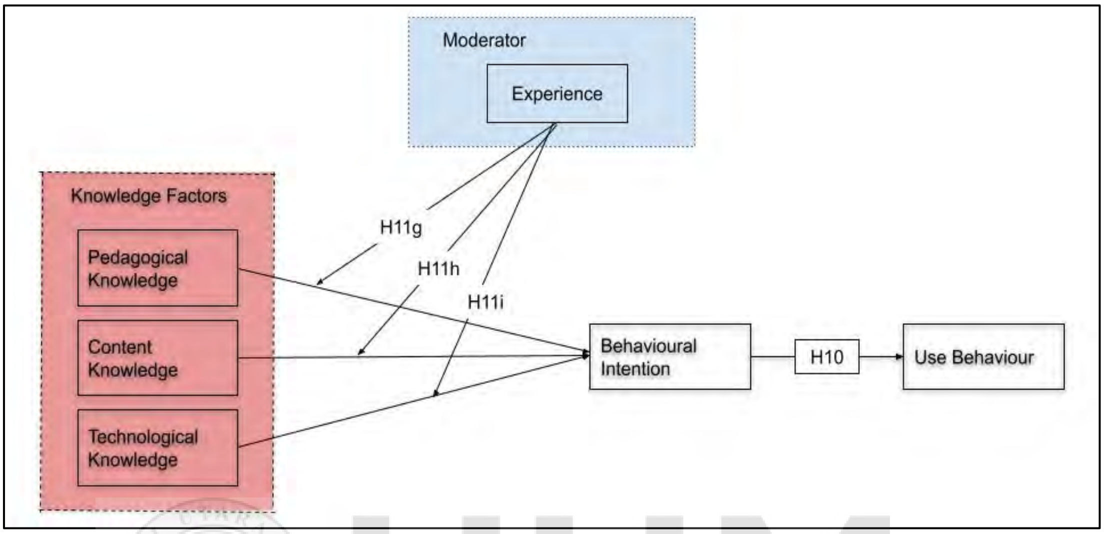

Figure 2.12 Teaching Experience as a Moderator

Figure 2.12 illustrates teaching experience as a moderating variable in the relationships between CK, PK, and TK and Behavioural Intention (BI) to adopt BL. Teaching experience is conceptualised as cumulative professional exposure that shapes instructional confidence, pedagogical refinement, and familiarity with educational technologies.

Content Knowledge (CK)

Empirical studies consistently indicate that academic staff with longer teaching experience report stronger content mastery (Liu et al., 2015). This accumulated expertise may influence how CK contributes to behavioural intention to adopt BL. Based on this, the following hypothesis was formulated:

H11g: Teaching experience moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI).

Pedagogical Knowledge (PK)

Pedagogical knowledge develops progressively through teaching practice, reflection, and ongoing professional learning. Research shows that highly experienced academic staff often report more refined pedagogical understanding (Liu et al., 2015), suggesting that experience may condition the influence of PK on behavioural intention to adopt BL. Consequently, the following hypothesis is proposed:

H11h: Teaching experience moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI).

Technological Knowledge (TK)

Based on Venkatesh et al. (2012), user experience conditions the relationship between knowledge and technology use. As a result, individuals with greater experience may exhibit higher confidence and lower hesitation in using technology, due to the accumulated skills and familiarity they have developed. It is therefore expected that academic staff with greater experience in technology use are more likely to form positive behavioural intentions towards its adoption. Years of practice and exposure may enhance academic staff's confidence and readiness to engage with instructional technologies. Consequently, the following hypothesis is proposed:

H11i: Teaching Experience moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

2.10 Critical Gaps and Contextual Evidence

This section synthesises the reviewed literature to identify key conceptual and empirical limitations that inform the positioning of the present study. Rather than claiming the absence of prior research, the discussion highlights patterns of emphasis, recurring omissions, and unresolved issues across studies on BL, technology acceptance, and academic staff engagement in higher education.

2.10.1 Emphasis on Student Adoption over Academic Staff Perspectives

The UTAUT2 has been extensively applied in consumer technology adoption research, as well as in educational contexts, to a lesser extent (Venkatesh et al., 2012; Tamilmani et al., 2020). Within Malaysian higher education, however, empirical applications of UTAUT and UTAUT2 have predominantly focused on students' adoption of LMS and online learning platforms (Hamdan et al., 2015; Raman & Lateh, 2015; Shakila et al., 2018; Tey & Moses, 2018). These studies provide valuable insights into student acceptance but offer a limited understanding of technology adoption from the perspective of academic staff.

Existing Malaysian studies examining the technology acceptance of academic staff are comparatively fewer and often employ earlier acceptance models or focus on specific technologies, rather than BL adoption as a broader teaching practice (Chan & Sya Azmeela Shariff, 2016; Raman & Rathakrishnan, 2018). Even fewer studies explicitly apply UTAUT2 to examine the adoption of academic staff in higher education, with Raman and Don (2013) representing one of the limited empirical efforts in this area. More recent regional reviews and empirical studies continue to report a dominance of student-centred technology adoption research and a relative lack of faculty-focused investigations, particularly in BL contexts (Chan et al., 2022; Vo et al., 2024; Anthony et al., 2024). This imbalance is theoretically and practically significant, given that academic staff play a central role in the design, implementation, and sustainability of BL initiatives.

Accordingly, a critical gap persists in understanding how UTAUT2 constructs explain academic staff's behavioural intention and use behaviour in Malaysian higher education, particularly within institutional environments where BL is formally promoted as a policy objective.

2.10.2 Limited Integration of Acceptance and Knowledge Frameworks

While UTAUT2 focuses on behavioural intention and technology use, it does not account for the professional knowledge required for meaningful technology integration in teaching. In contrast, the TPACK framework conceptualises the knowledge domains necessary for effective instructional use of technology (Mishra & Koehler, 2006). Numerous studies have applied TPACK to examine the readiness, competency development, and instructional practices of academic staff, both globally and within Malaysia (Chai et al., 2013; Koh et al., 2014; Scherer et al., 2017).

However, the literature reveals that TPACK studies have largely examined knowledge structures and direct effects, rather than their interaction with technology acceptance mechanisms or behavioural intention. At the same time, UTAUT2-based studies in education rarely incorporate pedagogical or content-related knowledge variables, treating technology adoption primarily as a behavioural or perceptual process (Scherer & Teo, 2019; Tamilmani et al., 2020).

A review of Malaysian BL research further indicates that no empirical study has systematically integrated UTAUT2 and TPACK to examine BL adoption among academic staff. Existing work tends to treat acceptance and knowledge as separate domains, resulting in fragmented explanations of why BL adoption remains inconsistent despite institutional investments and policy mandates. This conceptual separation limits the explanatory power of prior models and highlights the need for an integrated framework that simultaneously captures acceptance-driven and knowledge-driven dimensions of BL adoption.

2.10.3 Inconsistent Treatment of Knowledge and Demographic Influences

Demographic variables such as age, gender, and teaching experience have been widely examined as moderators within technology acceptance models, including UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012). These moderating effects are now well established across multiple contexts and technologies. In contrast, the literature indicates that demographic moderation within TPACK-based studies remains limited.

Most TPACK research has focused on measuring levels of technological, pedagogical, and content knowledge or examining their direct relationships with instructional practices and technology use (Chai et al., 2013; Koehler et al., 2014). Only a small number of studies have explored how demographic characteristics shape these knowledge domains, and even fewer have examined interaction effects between demographic variables and TPACK components, particularly in BL contexts (Scherer et al., 2017; Scherer & Teo, 2019).

Within the Malaysian context, TPACK studies have primarily adopted descriptive or correlational approaches, with limited attention given to moderation analysis or to how demographic variation influences academic staff's knowledge readiness for BL. This represents a significant empirical gap, as academic staff knowledge development is inherently shaped by professional experience, disciplinary background, and career stage.

2.10.4 Institutional Context and Implementation Realities

At the institutional level, national policy documents such as the Malaysia Education Blueprint 2015–2025 (Higher Education) and DePAN 2.0 emphasise BL as a core delivery mode in Malaysian higher education. Despite these directives, empirical studies continue to report challenges in translating policy aspirations into consistent teaching practice. Research conducted at UTHM and comparable public universities highlights issues related to uneven LMS usage, variable faculty engagement, and limited pedagogically focused training opportunities (Kirin et al., 2021; Ahmad et al., 2024; Wan & Nasri, 2023).

Existing institutional studies at UTHM have predominantly examined student experiences, including engagement, readiness, and perceptions of online learning. In contrast, systematic investigations into academic staff acceptance, knowledge readiness, and behavioural intention remain limited. This gap is particularly important given that institutional success in BL implementation depends not only on infrastructure but also on academic staff capability and willingness to integrate technology meaningfully into teaching.

2.10.5 Synthesis of Identified Gaps

Taken together, the literature reveals four interrelated gaps. First, UTAUT2 remains underutilised in explaining academic staff adoption of BL within Malaysian higher education. Second, existing studies rarely integrate technology acceptance models with professional knowledge frameworks such as TPACK. Third, the moderating influence of demographic variables on TPACK components remains empirically underexplored, particularly in BL contexts. Finally, institutional studies at UTHM have not sufficiently examined the perspectives of academic staff, despite their central role in the implementation of BL.

Addressing these gaps, the present study integrates UTAUT2 and TPACK within a single empirical framework, with demographic moderators applied exclusively to the knowledge components. By situating this investigation within the UTHM context, the study provides theoretically grounded and contextually relevant insights into academic staff acceptance and knowledge readiness for BL in Malaysian higher education.

2.11 Methodological Considerations Arising from the Literature

Drawing on the preceding theoretical and empirical review, this section synthesises key methodological implications emerging from prior studies on BL adoption. Rather than detailing the research design or analytical procedures, which are addressed in Chapter 3, this section clarifies how patterns, limitations, and inconsistencies in the existing literature informed the methodological direction of the present study. In particular, it highlights how previous research has shaped decisions related to model selection, construct integration, and analytical focus, thereby establishing a clear conceptual bridge between the literature review and the methodological framework adopted in this research.

Quantitative approaches have been widely employed to examine technology adoption in educational settings, particularly through established models such as UTAUT2 and TPACK, which respectively emphasise acceptance and knowledge readiness. These models have demonstrated strong explanatory power when applied independently. For example, Raman and Don (2013) applied UTAUT to examine the adoption of LMS among Malaysian pre-service academic staff, while Bervell et al. (2021) reported that TPACK explained a substantial proportion of variance in behavioural intention to adopt BL among higher education students. These studies confirm the robustness of both frameworks in explaining specific dimensions of technology adoption.

However, a closer examination of prior methodologies reveals several limitations relevant to the present study. First, many quantitative studies in the Malaysian higher education context have prioritised student samples, with academic staff either excluded or treated as a secondary group. While this approach is suitable for understanding learner readiness and engagement, it offers limited insight into the adoption decisions made by academic staff, who play a central role in designing, delivering, and sustaining BL practices. Consequently, existing findings cannot be readily generalised to explain academic staff behaviour without further empirical investigation.

Second, although UTAUT2 is effective in predicting behavioural intention and use, it does not explicitly account for knowledge-related domains, which are critical in educational environments. Conversely, TPACK-based studies focus primarily on professional knowledge readiness but often do not model behavioural intention or actual technology use as outcome variables. As a result, prior quantitative designs tend to capture either acceptance mechanisms or knowledge dimensions in isolation, rather than examining how these constructs jointly influence adoption behaviour among academic staff.

Third, while demographic variables such as age, gender, and teaching experience are frequently included as moderators in UTAUT and UTAUT2 studies, their analytical application has been largely confined to acceptance constructs. In contrast, TPACK studies have generally examined direct effects of knowledge components, with limited use of moderation analysis to explore how demographic characteristics shape the relationship between knowledge and behavioural intention. This methodological pattern suggests an opportunity to extend existing quantitative approaches by examining interaction effects that are theoretically meaningful within academic staff contexts.

At the institutional level, quantitative evidence has also highlighted persistent challenges affecting the implementation of BL, including uneven LMS utilisation, time constraints, and limited instructionally focused training for academic staff (Wan & Nasri, 2023; Zacharis & Nikolopoulou, 2022). While such findings are often reported descriptively, fewer studies have incorporated these realities into theoretically grounded models that explain academic staff adoption behaviour.

In response to these methodological limitations, the present study adopts a quantitative, theory-driven approach that integrates UTAUT2 and TPACK within a single research model. This integration enables the examination of both acceptance-related factors and knowledge components, while maintaining analytical clarity between the two frameworks. By focusing on academic staff within a Malaysian higher education institution, the study aligns its methodological design with the gaps identified in the literature and responds to calls for more context-sensitive and profession-specific adoption research.

Overall, this methodological positioning seeks to extend established quantitative models to a population and context that have received comparatively less systematic attention, while ensuring conceptual coherence and empirical rigour.

2.12 Conclusion

This chapter provides a critical review of the theoretical and empirical literature related to the adoption of BL in higher education, with a particular focus on technology acceptance and academic staff knowledge. The review demonstrates that no single theoretical framework is sufficient to explain the adoption of BL in educational contexts. Instead, adoption is shaped by the interaction of acceptance-related factors, knowledge readiness, and contextual influences within institutions.

Through a systematic synthesis of prior studies, this chapter has justified the selection of UTAUT2 as the primary acceptance framework and the integration of core TPACK knowledge components to address limitations in existing models. The review further identified gaps in the literature, particularly the limited empirical focus on academic staff adoption of BL in Malaysian higher education and the lack of integrated models that account for both behavioural intention and knowledge readiness.

Based on these insights, a conceptual framework was developed, and hypotheses were formulated to examine the direct and moderated relationships influencing the adoption of BL among academic staff at UTHM. This chapter, therefore, provides the theoretical and analytical foundation for the study, ensuring that the subsequent investigation is grounded in established scholarship while addressing clearly defined research gaps.

The next chapter presents the research methodology, detailing the research design, sampling procedures, instrumentation, and data analysis techniques employed to empirically test the proposed framework and hypotheses.

CHAPTER THREE
METHODOLOGY

3.0 Introduction

This chapter presents the methodological framework employed in this study, detailing the research design, sampling strategy, instrument development, pilot testing, and data analysis procedures. A quantitative explanatory research design was employed to investigate the factors influencing the adoption of BL among academic staff, guided by constructs from the UTAUT2 and TPACK frameworks.

The chapter explains the development of a structured questionnaire grounded in these theoretical frameworks and describes the pilot study conducted to establish the instrument's reliability and validity. The purpose, implementation, and findings of the pilot study are presented, including statistical assessments such as internal consistency reliability (Cronbach's alpha), composite reliability, and preliminary validity checks. Expert feedback and pilot responses were incorporated to refine the instrument prior to full-scale data collection.

Additionally, this chapter outlines the sampling strategy employed to select respondents and addresses key ethical considerations, including informed consent, voluntary participation, and confidentiality. Finally, the rationale for employing Partial Least Squares Structural Equation Modelling (PLS-SEM) as the primary data analysis technique is justified, given its suitability for theory testing and prediction-oriented research involving complex models. Overall, the methodological approach adopted in this study ensures coherence, rigour, and alignment with the research objectives.

3.1 Research Design

This study adopts an explanatory cross-sectional research design grounded in a positivist paradigm. An explanatory design is appropriate when the research objective is to test hypothesised relationships between variables derived from established theoretical frameworks (Creswell, 2014; Saunders et al., 2019). In this study, the explanatory approach is used to examine the relationships between UTAUT2 constructs, TPACK knowledge components, and academic staff's adoption of BL.

Although an exploratory review of the literature informed the development of the conceptual framework and hypotheses, the empirical phase of the study is explanatory in nature. It quantitatively tests theoretically grounded relationships using statistical modelling techniques. Data were collected at a single point in time through a structured questionnaire, consistent with a cross-sectional design commonly employed in technology acceptance and educational research (Venkatesh et al., 2012; Hair et al., 2017).

Accordingly, a quantitative survey method was employed to gather data from a large sample of university academic staff. Survey research is widely used in technology adoption studies to capture perceptions, attitudes, and behavioural intentions in a systematic and standardised manner (Creswell, 2009; Venkatesh et al., 2012). The use of a structured questionnaire enables the statistical examination of relationships among variables and supports the testing of multiple hypotheses within a single model.

The use of a standardised survey instrument also facilitates the application of multivariate analytical techniques, including Structural Equation Modelling (SEM), which is appropriate for testing complex theoretical models involving both direct and moderating relationships (Hair et al., 2017). In line with methodological best practices, the questionnaire underwent expert validation and pilot testing to ensure clarity, reliability, and construct alignment before its full deployment.

As a cross-sectional study, data capture a snapshot of BL adoption behaviour among academic staff at a specific point in time. While such designs do not establish causality in a temporal sense, the explanatory nature of the study, combined with theory-driven hypothesis testing and SEM analysis, allows for the examination of directional relationships within a robust conceptual framework. Overall, this research design is suitable for addressing the study's objectives, which aim to identify the key acceptance- and knowledge-related factors influencing the adoption of BL among academic staff.

The overall methodological process of the study is summarised in Figure 3.1, which outlines the key stages from theoretical grounding and instrument development to data collection and analysis.

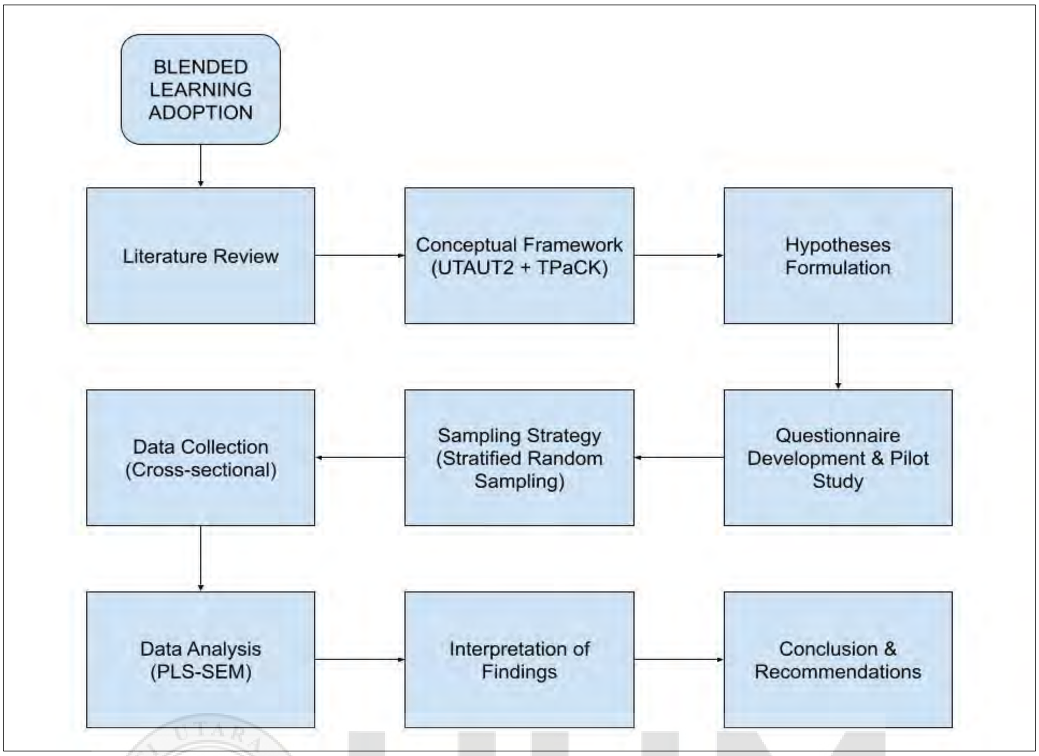

Figure 3.1 The research design process for the study on blended learning adoption based on the UTAUT2 and TPaCK frameworks

3.2 Research Method

Creswell (2009) categorises research methods into quantitative, qualitative, and mixed methods. This study adopted a quantitative approach to examine the success factors influencing the acceptance and use of BL and to evaluate the proposed success factors model. This method was deemed appropriate for investigating the relationship between independent and dependent variables (Bryman & Bell, 2015) and statistically analysing respondents' behaviour and attitudes (Lakshman et al., 2000). Creswell (2009) also emphasises that quantitative research validates conclusions by testing hypotheses and verifying established concepts. Additionally, several researchers have identified quantitative methods suitable for studying individual opinions, motives, and behaviours (Choudrie & Dwivedi, 2005; Mundar et al., 2014). Given these advantages, this approach was chosen to explore variations in BL acceptance and use among academic staff at UTHM.

Venkatesh et al. (2003) highlight the importance of consistency in research methods when developing a model. Venkatesh et al. (2012) noted that surveys have been widely used in technology acceptance studies. They effectively describe and explore human behaviour related to technology adoption (Nachmias & Nachmias, 2008). The need to gather data from many BL users made the survey method suitable for testing relationships between variables within a substantial sample.

Questionnaires are commonly used in technology acceptance research, often incorporating Likert scales ranging from five to seven points (Ahmed & Ghareb, 2017; Baharun et al., 2017; Dakduk et al., 2018; Lu et al., 2017; Wan Mohd Isa et al., 2016; Radovan & Kristl, 2017; Raman & Lateh, 2015; Raman & Rathakrishnan, 2018; Shen & Shariff, 2016). The Likert scale is a widely used, time-efficient survey tool that requires respondents to indicate their level of agreement with a set of statements (Bertram, 2010; Collis & Hussey, 2014).

For this study, a 6-point Likert scale was selected due to its advantages over other scales. The questionnaire included 43 statements rated from strongly agree (6) to strongly disagree (1). This scale offers a broader range of response options than a 4-point scale. It allows participants to express their views more precisely while reducing the risk of central tendency bias, where respondents might otherwise avoid extreme answers (Lei, 1994). It also reduces skewness and supports more balanced response distributions, improving measurement accuracy (Shin, 2011). The balanced response categories on a 6-point scale facilitate nuanced feedback, enhancing data validity and reliability (Lei, 1994). The interpretation of the scale is given in Table 3.1 below.

Table 3.1
Interpretation of the 6-Point Likert Scale

Scale	**Options**	**Score Range**	**Level**
1	Strongly Disagree	1.00-1.83	Very Low
2	Disagree	1.84-2.67	Low
3	Partially Disagree	2.68-3.50	Average
4	Partially Agree	3.51-4.33	Average
5	Agree	4.34-5.16	High
6	Strongly Agree	5.17-6.00	Very High

3.3 Sampling Design

3.3.1 Setting

This study was conducted at UTHM, a public university located in the suburban district of Batu Pahat, Johor, Malaysia. UTHM comprises eight faculties encompassing disciplines such as engineering, education, science, and technology management, alongside several academic centres, including the Centre for Language Studies, Centre for Co-Curricular Studies, and postgraduate academic units. These faculties and centres collectively offer diploma, undergraduate, and postgraduate programmes.

The target population consisted of academic staff across all faculties and academic centres at UTHM, including lecturers, senior lecturers, associate professors, professors, and equivalent academic appointments. Including academic staff from diverse disciplinary backgrounds and academic roles enabled the study to capture variation in technological exposure and professional experience, relevant to the adoption of BL.

UTHM provides an appropriate institutional context for this investigation, as the university has actively promoted BL through institutional policies, LMS, and professional development initiatives. However, BL adoption varies across faculties and individuals, making UTHM a suitable setting for examining acceptance- and knowledge-related factors influencing BL adoption. The multi-faculty context is particularly relevant given the integration of the TPACK framework, where disciplinary content knowledge contexts may shape adoption behaviour.

3.3.2 Sampling Technique

This study employed a stratified random sampling technique to ensure proportional representation of academic staff across faculties and academic centres at UTHM. Stratified sampling is particularly suitable for heterogeneous populations, as it involves dividing the population into relatively homogeneous subgroups (strata) before randomly selecting respondents within each stratum (Cochran, 1977; Etikan & Bala, 2017).

In the context of UTHM, academic staff are distributed across faculties and centres that differ in disciplinary focus, knowledge domains, and exposure to BL initiatives. Treating each faculty and academic centre as a distinct stratum ensured balanced representation of all academic units, minimised selection bias, and strengthened the internal and external validity of the study (Taherdoost, 2016; Groves, 1989).

Stratified sampling also improves statistical precision by reducing within-group variability prior to sample selection, thereby lowering the standard error of estimates compared to simple random sampling (Cochran, 1977; Singh & Masuku, 2014). This advantage is particularly relevant for Structural Equation Modelling (SEM), which requires stable parameter estimation when examining complex relationships among multiple constructs. Within each stratum, respondents were selected using simple random sampling, ensuring that every eligible academic staff member had an equal chance of being selected (Heeringa et al., 2004).

3.3.3 Sample Size Determination and Population

The target population for this study consisted of 1,162 academic staff members at UTHM, encompassing all faculties and academic centres. To determine an appropriate minimum sample size, Krejcie and Morgan's (1970) sample size determination table was employed.

Based on these guidelines, a minimum sample size of 396 respondents is recommended for a population of 1,162. This sample size is considered sufficient to achieve adequate statistical power and precision in survey-based quantitative research. It is also appropriate for multivariate techniques such as Structural Equation Modelling (SEM), which require an adequate sample-to-parameter ratio for reliable estimation (Cochran, 1977; Hair et al., 2017).

The minimum target sample of 396 respondents was proportionately allocated across faculties and academic centres in accordance with the stratified sampling design. The procedures used to operationalise this sampling plan, including response management and data screening, are described in the following section.

3.3.4 Sampling Procedure

Following proportional allocation across strata, questionnaires were distributed to academic staff selected through a stratified random sampling process. Although the minimum required sample size was 396, the study adopted a controlled oversampling strategy to account for anticipated non-response and incomplete questionnaires. Accordingly, an additional 25 academic staff members were randomly selected from the same stratified sampling frame, resulting in a total of 421 questionnaires distributed. This oversampling approach is a recognised practice in survey-based research to safeguard against attrition and ensure that the final usable dataset meets minimum statistical requirements after data screening (Dillman et al., 2014; Hair et al., 2017). Importantly, the additional respondents were selected using the same stratified random procedure, with no preferential selection applied, and proportional representation was maintained across strata.

Following data collection, responses were screened for completeness and data quality. Incomplete questionnaires and cases with excessive missing data were excluded. After data cleaning, the final dataset consisted of 300 valid responses, which were retained for analysis based on the variance-based SEM requirements. This final sample size met the minimum thresholds recommended for variance-based SEM, satisfying requirements for model estimation, statistical power, and robustness in PLS-SEM analysis (Hair et al., 2017; Kock & Hadaya, 2018).

3.3.5 Data Collection Method and Technique

Data collection was conducted using an online questionnaire administered via Google Forms. Although face-to-face data collection was initially planned, constraints imposed by the COVID-19 pandemic necessitated a shift to online administration.

Online surveys offer a practical, safe, and efficient means of collecting data from large samples, particularly in higher education contexts (Dillman et al., 2014).

The survey link was distributed via institutional email to the selected respondents within each stratum. Follow-up reminder emails were sent at one-week intervals to encourage participation from non-respondents. Data collection was conducted over a four-week period, from 1 November to 23 November 2021.

Using Google Forms reduced logistical constraints associated with physical data collection, minimised data entry errors, and enhanced response anonymity, which may improve the accuracy and honesty of responses (Bryman & Bell, 2015; Wright, 2005). The platform also facilitated efficient monitoring of response rates and automated data export for subsequent analysis. Given the study's focus on technology adoption in a university setting, online data collection was both methodologically appropriate and contextually relevant.

3.4 Ethical Considerations

This research followed all institutional ethical guidelines. Ethical consent was obtained prior to conducting any survey, and all necessary requirements were followed before data collection commenced. Participants were informed about the research and provided their consent before completing the questionnaire. Participants were allowed to participate in this study voluntarily and were assured of confidentiality throughout the data collection process.

Participants were provided with a consent form and assured that their responses would be kept anonymous and confidential, and that their data would be used solely for research purposes. They were given approximately 20 minutes to complete the questionnaire, which was designed to be user-friendly and accessible via various devices.

3.4.1 Informed Consent Process

Each participant received a comprehensive information sheet detailing the study's purpose, methods, potential risks and benefits, and their rights as research participants. The consent process emphasised voluntary participation, with participants free to withdraw without consequences. All information was presented in clear, non-technical language to ensure full understanding.

3.4.2 Confidentiality and Data Protection

To ensure participant confidentiality, several measures were implemented throughout the research process. First, data anonymisation was done using a coding system that removed personal identifiers, ensuring that individual responses could not be traced back to specific participants. Additionally, all collected data were stored securely in password-protected files and encrypted systems, preventing unauthorised access. To further safeguard confidentiality, access to raw data was strictly limited to authorised research personnel, minimising the risk of data breaches or misuse. Finally, the reporting of findings was conducted in an aggregate form, preventing the identification of individual participants and ensuring that all results remained generalised within the broader dataset. These measures strengthened the study's ethical integrity and upheld the principles of research confidentiality.

3.4.3 Data Management

All collected data were handled with strict confidentiality throughout the research process. The questionnaire responses were stored securely, and any identifying information is separated from the research data. Data will be retained in accordance with institutional requirements and will be destroyed securely when no longer needed. This ethical framework protects participants' rights while maintaining research integrity and scientific rigour. The study's commitment to these ethical principles helps build trust with participants and supports the collection of honest, valuable data for understanding BL adoption factors at UTHM.

3.5 Questionnaire Development

The questionnaire was developed based on the theoretical framework of the study and the identified constructs, as discussed in Chapter 2. Designing a valid and reliable questionnaire is crucial, as it must be carefully crafted and tailored to effectively address the research objectives. This study separated the questionnaire into two parts: A and B.

3.5.1 Section A: Demographic Information

Section A of the questionnaire collected demographic information to describe the respondents' profiles and to support sampling verification and subsequent analysis. The demographic variables included age, gender, faculty affiliation, years of teaching experience, and academic designation. Among these variables, age, gender, and teaching experience were theoretically integrated into the research framework and analysed as moderating variables, consistent with prior technology acceptance and educational technology research (Venkatesh et al., 2012; Scherer et al., 2017). Faculty affiliation and academic designation were collected for descriptive purposes and to ensure proportional representation across academic units and roles; however, they were not included in the inferential analysis.

Age, gender, and teaching experience were included as key demographic variables because they were theoretically integrated into the research model and explicitly examined as moderating factors in the relationships between TPACK knowledge components and behavioural intention. Age was categorised into three groups (below 35 years, 36–50 years, and above 50 years) to reflect generational differences in professional experience, digital exposure, and confidence in adopting educational technologies (Cheng & Xie, 2018; Scherer et al., 2019).

Teaching experience was grouped into less than 5 years, 5–15 years, and more than 15 years to distinguish early-career, mid-career, and highly experienced academic staff. This categorisation is consistent with prior educational technology studies and supports meaningful comparison of professional knowledge development and adoption behaviour across career stages (Venkatesh et al., 2012; Lee & Hung, 2015).

Gender was included to account for documented differences in technology-related perceptions, confidence, and adoption patterns reported in previous technology acceptance research (Venkatesh et al., 2012; Scherer et al., 2019).

Other demographic variables that were not theoretically integrated into the research model or analysed in subsequent stages were deliberately excluded to maintain conceptual clarity and alignment between data collection, analysis, and interpretation.

3.5.2 Section B: Conceptual Constructs and Measurement Dimensions

The second section contained structured items that measured key factors influencing the adoption of BL. The questionnaire was developed based on the UTAUT2 and the TPACK framework, ensuring alignment with established research models. Each item was categorised under eleven conceptual dimensions that captured both technology adoption and professional knowledge components:

1. Performance Expectancy (PE): Perceived benefits of BL in improving work-related and instructional performance.
2. Effort Expectancy (EE): Perceived ease of use and skill acquisition for BL adoption.
3. Social Influence (SI): The impact of peers and institutional expectations on BL usage.
4. Facilitating Conditions (FC): Availability of resources and institutional support for BL.
5. Hedonic Motivation (HM): The extent to which BL is perceived as enjoyable or engaging.
6. Habit (HT): The extent to which BL has become a routine practice.
7. Technological Knowledge (TK): Proficiency in using technology to conduct BL.
8. Pedagogical Knowledge (PK): Knowledge of teaching strategies and instructional adaptability in BL settings.
9. Content Knowledge (CK): Subject matter expertise and its integration within BL contexts.
10. Behavioural Intention (BI): The intention to continue using BL.
11. Actual Use (AU): The frequency and extent of BL adoption in academic work activities.

3.5.3 Items Development and Data Coding

Data coding was applied by assigning alphanumeric values to each survey item to ensure accuracy in statistical analysis. This enabled systematic data entry, consistency, and streamlined interpretation. The questionnaire employed a six-point Likert scale, which excluded a neutral midpoint to reduce central tendency bias and enhance the clarity of respondents' attitudes and behaviours. This structure also facilitated robust statistical analysis within a variance-based SEM framework, increasing the reliability and validity of the study's findings.

The coding approach assigned numerical values from 1 (Strongly Disagree) to 6 (Strongly Agree), as illustrated in Figure 3.2. The midpoint of the scale is 3.5; therefore, a mean score above 3.5 indicates a tendency toward agreement, while a score of 6 indicates full agreement.

Strongly disagree					**Strongly agree**
1	**2**	**3**	**4**	**5**	**6**

Figure 3.2 Likert Scale 6 Points

The decision to omit a neutral midpoint is supported by both theoretical and empirical arguments. From a measurement perspective, Likert-type categories can be conceptualised similarly to physical measurement tools (e.g., rulers), which do not contain neutral points (Wolfe & Smith, 2007). Additionally, Linacre (2013) notes that neutral categories may interfere with model fit or yield disordered responses in statistical analyses.

Furthermore, if items are carefully developed and piloted, all respondents should be able to form an opinion, rendering a neutral option unnecessary (Wolfe & Smith, 2007). Contemporary approaches to psychological and educational measurement can also manage small amounts of missing data, further supporting the exclusion of a neutral response.

Empirical studies show that six-point Likert scales yield higher reliability than five-point alternatives (Chomeya, 2010; Gries et al., 2018). The absence of a neutral option compels respondents to take a position, reducing the likelihood of non-committal responses and potentially generating more meaningful insights (Chomeya, 2010). Moreover, even-numbered scales support clearer interpretation by allowing response categories to be grouped as favourable, unfavourable, or uncertain (Gries et al., 2018). In studies exploring perceptions of innovative educational approaches, such as BL, this format encourages deeper reflection, particularly when neutrality might mask hesitation or disengagement.

The final questionnaire comprised 43 items, adapted from established constructs in the UTAUT2 model (Venkatesh et al., 2012) and the TPACK model (Schmidt et al., 2009; Garrett, 2014). Of these**,** the majority of items measured the independent variables, which included:

- Performance Expectancy (PE)
- Effort Expectancy (EE)
- Social Influence (SI)
- Facilitating Conditions (FC)
- Hedonic Motivation (HM)
- Habit (HT)
- Technological Knowledge (TK)

- Pedagogical Knowledge (PK)
- Content Knowledge (CK)

The remaining three items measured the dependent variables:

- Behavioural Intention (BI) to adopt BL, and
- Actual Use (AU) of BL.

The questionnaire was developed in English, the official second language in Malaysia, and was appropriate for the academic and professional context of the respondents. It comprised items measuring independent variables across nine constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK)—and items measuring the dependent variables, Behavioural Intention (BI) and Actual Use (AU). Most constructs used a six-point agreement-based Likert scale, while Actual Use employed a frequency scale (e.g., Never to Always) to better capture behavioural indicators.

Items were primarily adapted from validated instruments to ensure theoretical rigour and contextual relevance. The UTAUT2 constructs were adapted from Venkatesh et al. (2012), with rewording to suit the BL context. For instance, general terms like "using the system" were revised to "using blended learning" to reflect the BL adoption context of this study. The TPACK constructs (TK, PK, CK) were adapted from Schmidt et al. (2009) and Garrett (2014), with adjustments made to align with disciplinary knowledge contexts and subject specialisations in Malaysian higher education.

Adapting rather than adopting items verbatim is a widely endorsed practice in measurement development (DeVellis, 2017; Bryman & Bell, 2015). This allows researchers to preserve the core conceptual meaning of each construct while ensuring that item wording resonates with the specific research context. As Hair et al. (2017) highlight, construct validity must be re-established when instruments are used in new settings. To support this, expert panels (see Section 3.6.1) reviewed all items to confirm their clarity, content validity, and relevance to the adoption of BL in higher education.

3.5.3.0 Performance Expectancy

Measurement of academic staff's performance expectancy toward the behavioural intention to use BL was adapted from Venkatesh et al. (2012).

Table 3.2
Items for Performance Expectancy

Code	Items
PE1	Using BL would improve my teaching performance
PE2	Using BL helps me to accomplish teaching tasks more quickly
PE3	Using BL increases my productivity
PE4	Using BL would enhance my effectiveness in teaching

3.5.3.1 Effort Expectancy

The academic staff's effort expectancy toward the behavioural intention to use BL was measured using items adapted from Venkatesh et al. (2012).

Table 3.3
Items for Effort Expectancy

Code	Items
EE1	Learning how to use BL for my class is easy for me
EE2	It is easy for me to become skilful at implementing BL
EE3	I find BL easy to use in my class
EE4	My interaction with BL is clear and understandable

3.5.3.2 Social Influence

The social influence of academic staff on behavioural intention to use BL was measured using items adapted from Venkatesh et al. (2012, 2013).

Table 3.4
Items for Social Influence

Code	Items
SI1	People who are important to me think I should use BL
SI2	People who influence my behaviour think that I should use BL
SI3	People whose opinions I value prefer that I use BL
SI4	In general, the organisation has supported the use of BL

3.5.3.3 Facilitating Conditions

Measurement of academic staff's facilitating conditions toward behavioural intention to use BL was adapted from Venkatesh et al. (2012).

Table 3.5
Items for Facilitating Conditions

Code	**Items**
FC1	I have the resources necessary to use BL in my class
FC2	BL is compatible with other technologies I use
FC3	I can get help from others when I have difficulties using BL

3.5.3.4 Hedonic Motivation

The measurement of academic staff's hedonic motivation toward the behavioural intention to use BL was adapted from Venkatesh et al. (2012).

Table 3.6
Items for Hedonic Motivation

Code	**Items**
HM1	Using BL is fun
HM2	Using BL is enjoyable
HM3	Using BL is very entertaining

3.5.3.5 Habit

Measurement of academic staff's habits toward behavioural intention to use BL was adapted from Venkatesh et al. (2012).

Table 3.7
Items for Habit

Code	Items
HT1	The use of BL has become a habit for me
HT2	I must use BL
HT3	Using BL has become natural to me

3.5.3.6 Technological Knowledge

Measurement of academic staff's technological knowledge towards the behavioural intention to use BL was adapted from Schmidt et al. (2009) and Garrett (2014).

Table 3.8
Items for Technological Knowledge

Code	Items
TK1	I know how to solve ICT-related problems during BL sessions
TK2	I keep up with important new technologies that are useful for BL sessions
TK3	I know a lot of different technologies that I can use for BL
TK4	I have the technical skills I need to use technology for a successful BL session

3.5.3.7 Pedagogical Knowledge

Measurement of academic staff's pedagogical knowledge towards the behavioural intention to use BL was adapted from Schmidt et al. (2009) and Garrett (2014).

Table 3.9
Items for Pedagogical Knowledge

Code	Items
PK1	I know how to assess student's performance
PK2	I can adapt my teaching based upon what students currently understand or do not understand
PK3	I can adapt my teaching style to different learners
PK4	I can assess student learning in multiple ways
PK5	I can use a wide range of teaching approaches
PK6	I am familiar with a wide range of practices, strategies, and methods of teaching
PK7	I know how to motivate students to learn

3.5.3.8 Content Knowledge

The measurement of academic staff's content knowledge in relation to the behavioural intention to use BL was adapted from Schmidt et al. (2009) and Garrett (2014).

Table 3.10
Items for Content Knowledge

Code	Items
CK1	I have sufficient knowledge in developing content in my discipline
CK2	I have various ways and strategies of developing my understanding of my discipline
CK3	I know the basic theories and concepts of my discipline
CK4	I know the history and development of important theories in my discipline
CK5	I am familiar with recent research in my discipline

3.5.3.9 Behavioural Intention

Measurement of behavioural intention toward BL use was adapted from Venkatesh et al. (2012).

Table 3.11
Items for Behavioural Intention

Code	Items
BI1	I intend to continue using BL in the future
BI2	I will always try to use BL in my daily work
BI3	I plan to continue to use BL frequently

Each construct was measured using multiple items (indicators) to ensure sufficient coverage and conceptual clarity. The final instrument drew primarily from UTAUT2 (Venkatesh et al., 2012) and TPACK-based instruments (Mishra & Koehler, 2006; Schmidt et al., 2009; Garrett, 2014), with adaptations made to reflect the context of BL among academic staff at UTHM.

Table 3.12 summarises the adaptation decisions for each construct along with their respective justification and sources.

Table 3.12
Decisions and justification for each construct

Construct	Model	Adopted / Adapted	Justification & Source
Performance Expectancy (PE)	UTAUT2	Adapted	Items adapted from Venkatesh et al. (2012) to reflect BL use in academic work contexts. Supported by: Akintunde and Egunjobi (2018); recent peer-reviewed studies in educational technology journals (e.g., Frontiers in Education).
Effort Expectancy (EE)	UTAUT2	Adapted	Language adapted to reflect the ease of using and learning BL systems in higher education. Supported by: Venkatesh et al. (2012); recent peer-reviewed studies in educational technology journals (e.g., Frontiers in Education).
Social Influence (SI)	UTAUT2	Adapted	Adapted to address institutional and peer influence in the university context. Supported by: Venkatesh et al. (2012); recent peer-reviewed studies in educational technology journals (e.g., Frontiers in Education).
Facilitating Conditions (FC)	UTAUT2	Adapted	Modified to include support for BL infrastructure and institutional support mechanisms. Supported by: Venkatesh et al. (2012); recent peer-reviewed studies in educational technology journals (e.g., Frontiers in Education).
Hedonic Motivation (HM)	UTAUT2	Adapted	Slightly reworded to reflect enjoyment of using BL as an academic technology. Supported by: Venkatesh et al. (2012); empirical studies on hedonic motivation in technology acceptance research.
Habit (HT)	UTAUT2	Adapted	Framed in terms of past experience with technology use in academic work. Supported by: Venkatesh et al. (2012); recent empirical

			studies on habit in technology acceptance research.
Behavioural Intention (BI)	UTAUT2	Adapted	Tailored to assess intention to use BL in future academic activities. Supported by: Venkatesh et al. (2012).
Actual Use (AU)	UTAUT2	Adapted	Measured via frequency items contextualised to BL application. Supported by: Venkatesh et al. (2012).
Technological Knowledge (TK)	TPACK	Adapted	Adapted from Schmidt et al. (2009) and Garrett (2014) to focus on digital technology knowledge relevant to BL. Supported by: Mishra and Koehler (2006).
Pedagogical Knowledge (PK)	TPACK	Adapted	Wording adjusted to suit the Malaysian higher education context and self-reported pedagogical knowledge. Supported by: Schmidt et al. (2009); Garrett (2014).
Content Knowledge (CK)	TPACK	Adapted	Items contextualised for higher education lecturers in disciplinary content knowledge. Supported by: Schmidt et al. (2009); Mishra and Koehler (2006).

AU1 Integration of BL Tools

"To what extent do you integrate various BL tools (e.g., learning management systems, online forums, multimedia resources) into your teaching practices?"

- ☐ 1 - Not at all
- ☐ 2 - Very slightly
- ☐ 3 - Slightly
- ☐ 4 - Moderately
- ☐ 5 - Very much
- ☐ 6 - Extremely

AU2 Student Engagement with BL Content

"How frequently do your students engage with BL content outside of the classroom (e.g., accessing online materials, completing online assignments, participating in online discussions)?"

- ☐ 1 - Never
- ☐ 2 - Very rarely
- ☐ 3 - Rarely
- ☐ 4 - Sometimes
- ☐ 5 - Often
- ☐ 6 - Always

AU3 Adaptation and Customisation of BL Strategies
"How often do you adapt and customise BL strategies to meet the specific needs of your courses and students?"

- 1 - Never
- 2 - Very rarely
- 3 - Rarely
- 4 - Sometimes
- 5 - Often
- 6 – Always

Adapting items, rather than adopting them verbatim, enables semantic alignment with the study population and local educational practices. For instance, while the original UTAUT2 model was developed for general technology use, this study required rewording items to specify “blended learning” rather than general “technology.” In the case of Actual Use, items refer to observable teaching-related activities; however, these items are interpreted as indicators of academic staff’s technology use behaviour rather than pedagogical effectiveness. Similarly, while TPACK constructs such as TK and PK are globally used, they have been adjusted to align with Malaysian university settings and the implementation norms of BL.

The decision to adapt rather than adopt is also supported by the need for content validity in new contexts. According to DeVellis (2017), adapting validated instruments to suit the domain and population under study, while maintaining their theoretical core, is standard practice in educational and behavioural research.

All adapted items were reviewed by an expert panel (as described in the Pilot Study section) to confirm that they accurately and appropriately reflect each construct in the context of BL adoption in higher education.

3.6 Pilot Study

A pilot study was conducted to assess the clarity, reliability, and preliminary validity of the research instrument prior to full-scale data collection. Pilot testing is a crucial step in survey-based research, as it enables researchers to identify potential measurement issues, refine questionnaire items, and ensure that respondents interpret the items as intended (Creswell, 2009). In line with best practices in quantitative research, the pilot study served as a quality control mechanism to ensure the questionnaire was administered effectively to the main sample.

3.6.1 Expert Validation

Prior to the pilot study, the questionnaire underwent a structured expert validation process to enhance its content validity, methodological suitability, and linguistic clarity. Expert validation is a critical step in survey instrument development, particularly in theory-driven quantitative research, as it ensures that items accurately represent constructs, align with analytical requirements, and are clearly interpreted by respondents (Crocker & Algina, 2008; DeVellis, 2016).

Three experts were purposefully selected based on the specific validation needs of this study. The first expert was a quantitative researcher with extensive experience in Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS. This expert reviewed the instrument from a methodological and measurement perspective, focusing on scale design, construct operationalisation, and suitability for variance-based SEM analysis. Based on this review, two key recommendations were made. First, the expert advised using a six-point Likert scale instead of a seven-point scale to reduce central tendency bias and discourage neutral responses, which is consistent with best practices in behavioural intention and technology adoption research. Second, the expert recommended omitting certain demographic questions that were not directly aligned with the study's objectives or analytical framework, thereby improving parsimony and reducing respondent burden.

The second expert specialised in BL and online learning in higher education. This expert reviewed the conceptual clarity, contextual relevance, and practical appropriateness of the questionnaire items, particularly those measuring the adoption of BL and actual use. One key recommendation was to provide a clear and explicit definition of "blended learning" at the beginning of the questionnaire to ensure a shared understanding among participants and to minimise variation in interpretation.

Importantly, this expert also advised against including a binary screening question such as "Have you ever used blended learning?" The justification for this recommendation was contextual and institution-specific. At UTHM, academic staff have been required to implement technology-enhanced and BL practices, including the FOC initiative, since 2017. As a result, the use of a binary "yes/no" question was considered inappropriate and uninformative, as it would not meaningfully differentiate academic staff in terms of their actual engagement with BL. Instead, such a question could introduce measurement artefacts by implying variability where institutional policy had already standardised exposure.

Following this advice, the measurement of Actual Use (AU) was reconceptualised to reflect the extent and frequency of BL use behaviour rather than mere exposure. The original dichotomous screening approach was replaced with continuous Likert-scale items capturing (i) the extent of integration of BL tools, (ii) student engagement with BL content, and (iii) the adaptation and customisation of BL strategies. This revision enabled the construct to more accurately reflect self-reported BL use patterns and align with the continuous measurement assumptions required for SEM analysis.

The third expert was a language specialist who reviewed the questionnaire for grammatical accuracy, clarity of phrasing, and readability within the Malaysian higher education context. This review focused on eliminating ambiguous wording, simplifying sentence structures, and ensuring consistent terminology across constructs and response options. Minor revisions were made to improve clarity and reduce the risk of misinterpretation, particularly in Likert-scale anchors and instructional statements.

All feedback from the three experts was systematically incorporated into the revised questionnaire prior to pilot testing. These refinements strengthened the instrument's methodological rigour, contextual appropriateness, and linguistic precision, ensuring its suitability for large-scale data collection and subsequent PLS-SEM analysis.

3.6.2 Pilot Study Implementation

The pilot study was administered using Google Forms to mirror the data collection procedure planned for the main study. Conducting the pilot online allowed the researcher to evaluate not only the clarity and relevance of the questionnaire items but also the functionality, flow, and usability of the digital survey format (Fink, 2006).

A total of 30 academic staff members from UTHM, who were not included in the main study sample, were invited to participate. This sample size is consistent with methodological recommendations for pilot testing, which suggest involving between

10 and 30 participants to identify potential issues in survey instruments without overburdening resources (Hill, 1998; Monette, Sullivan, & DeJong, 2002).

Participants were given one week to complete the pilot survey and were encouraged to provide qualitative feedback through open-ended comments. Feedback was primarily related to item clarity, terminology, and the length of the survey. For example, one participant suggested clarifying the term “pedagogical support” in a Facilitating Conditions item, while others noted the need to more clearly differentiate between Pedagogical Knowledge and Content Knowledge. These comments informed minor revisions to improve item clarity and conceptual distinction prior to the main data collection.

3.6.3 Pilot Study Findings

The pilot study data were analysed to evaluate the internal consistency reliability of the measurement instrument prior to full-scale data collection. Reliability analysis was conducted using SPSS, a statistical software package widely used in quantitative research (Field, 2018). Internal consistency was assessed using Cronbach’s alpha (α), which measures the degree to which items within a construct are interrelated and consistently represent the same underlying concept (Cronbach, 1951).

Cronbach’s alpha values were interpreted based on established guidelines in psychometric and social science research. According to Nunnally and Bernstein (1994), alpha values of 0.70 and above indicate acceptable internal consistency for exploratory and early-stage research, values above 0.80 indicate good reliability, and values exceeding 0.90 reflect excellent internal consistency. These thresholds are widely adopted in educational and technology acceptance studies (Tavakol & Dennick, 2011; Hair et al., 2017).

Table 3.13 presents the reliability results for each construct measured in the pilot study.

Table 3.13
Pilot Study Results

Variable	**Cronbach's Alpha**	**Interpretation**
Social Influence (SI)	0.8544	Good internal consistency
Hedonic Motivation (HM)	0.9747	Excellent internal consistency
Actual Use (AU)	0.8261	Good internal consistency
Effort Expectancy (EE)	0.9229	Excellent internal consistency
Performance Expectancy (PE)	0.8195	Good internal consistency
Behavioural Intention (BI)	0.9559	Excellent internal consistency
Technological Knowledge (TK)	0.7197	Acceptable internal consistency
Habit (HT)	0.8758	Good internal consistency
Content Knowledge (CK)	0.7336	Acceptable internal consistency
Facilitating Conditions (FC)	0.7682	Acceptable internal consistency

The constructs Hedonic Motivation (HM) ($\alpha = 0.9747$) and Behavioural Intention (BI) ($\alpha = 0.9559$) demonstrated excellent internal consistency, indicating a very high degree of inter-item correlation and strong reliability (Nunnally & Bernstein, 1994). While very high alpha values may sometimes suggest item redundancy, Tavakol and Dennick (2011) note that such values are acceptable in pilot testing, particularly when constructs are theoretically well-defined, and multidimensionality is further assessed in subsequent analyses.

Effort Expectancy (EE) ($\alpha = 0.9229$) and Performance Expectancy (PE) ($\alpha = 0.8195$) also showed strong reliability, consistent with previous UTAUT2-based studies that reported high internal consistency for these constructs in technology adoption contexts (Venkatesh et al., 2012; Hair et al., 2017).

Social Influence (SI) ($\alpha = 0.8544$), Actual Use (AU) ($\alpha = 0.8261$), and Habit (HT) ($\alpha = 0.8758$) exhibited good internal consistency, indicating that the items within each construct were well-aligned and reliably measured the intended concepts (Tavakol & Dennick, 2011).

Technological Knowledge (TK) ($\alpha = 0.7197$), Content Knowledge (CK) ($\alpha = 0.7336$), and Facilitating Conditions (FC) ($\alpha = 0.7682$) demonstrated acceptable internal consistency. According to Nunnally and Bernstein (1994), alpha values slightly above 0.70 are acceptable for newly adapted instruments or constructs with broader conceptual domains, such as knowledge-related measures. These results suggest that the items were sufficiently reliable, although minor refinement could further enhance precision.

In addition to Cronbach's alpha, a preliminary analysis using SmartPLS was conducted to assess construct validity. Composite Reliability (CR) values exceeded the recommended threshold of 0.70, and Average Variance Extracted (AVE) values were above 0.50, indicating satisfactory convergent validity (Hair et al., 2017). Discriminant validity was supported using the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios, with no evidence of problematic cross-loadings.

Overall, the pilot study confirmed that the questionnaire demonstrated strong internal consistency and satisfactory preliminary validity across all constructs. Minor revisions were made based on pilot feedback, including refining the wording of selected Technological Knowledge and Facilitating Conditions items and clarifying key terminology. These refinements enhanced clarity and face validity, ensuring that the instrument was suitable for full-scale data collection in the main study.

3.7 Data Analysis

This study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse the proposed research model. PLS-SEM is a variance-based SEM technique that is particularly suitable for prediction-oriented research, complex models with multiple constructs, and studies integrating different theoretical frameworks (Hair et al., 2017; Henseler et al., 2016). Given the study's objective to explain and predict BL adoption by integrating UTAUT2 and TPACK constructs, PLS-SEM was deemed an appropriate analytical approach.

Data analysis was conducted using SmartPLS software and followed a systematic three-stage procedure: (1) assessment of the measurement model, (2) evaluation of the structural model, and (3) hypothesis testing using bootstrapping. This sequence aligns with established PLS-SEM reporting guidelines (Hair et al., 2017).

3.7.1 PLS-SEM Analysis Procedure

The PLS-SEM analysis proceeded in three main stages. First, the measurement model was evaluated to ensure the reliability and validity of all latent constructs. Second, the structural model was assessed to examine the hypothesised relationships between constructs and the model's explanatory and predictive power. Finally, bootstrapping was applied to test the statistical significance of the hypothesised paths.

3.7.1.0 Measurement Model Assessment

The measurement model assessment aimed to verify that the indicators reliably and validly measured their respective latent constructs. This evaluation involved examining internal consistency reliability, convergent validity, and discriminant validity.

Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR). Values of 0.70 or higher indicate acceptable reliability, while values above 0.80 suggest good reliability (Nunnally & Bernstein, 1994; Hair et al., 2017). Composite Reliability was prioritised in interpretation, as it does not assume equal indicator loadings and is therefore more appropriate for SEM analysis.

Convergent validity was evaluated using Average Variance Extracted (AVE). An AVE value of 0.50 or higher indicates that a construct explains at least half of the variance of its indicators, demonstrating adequate convergent validity (Fornell & Larcker, 1981).

Discriminant validity was examined using two criteria. First, the Fornell–Larcker criterion was applied, requiring the square root of each construct's AVE to exceed its correlations with other constructs. Second, the Heterotrait–Monotrait (HTMT) ratio was assessed, with values below 0.85 indicating sufficient discriminant validity (Henseler et al., 2015). Together, these tests ensured that each construct was empirically distinct and measured a unique concept within the model.

3.7.1.1 Structural Model Assessment

After establishing the adequacy of the measurement model, the structural model was assessed to evaluate the hypothesised relationships between constructs. Structural model evaluation in PLS-SEM focuses on collinearity diagnostics, path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) (Hair et al., 2017).

Collinearity among predictor constructs was examined using the Variance Inflation Factor (VIF) values. VIF values below 5, and preferably below 3, indicate that multicollinearity is not a concern (Hair et al., 2017). In this study, all VIF values fell within acceptable thresholds, confirming that the predictor constructs made unique contributions to explaining the endogenous variables.

Path coefficients (β) were then examined to determine the strength and direction of the hypothesised relationships. These coefficients represent the direct effects of exogenous constructs on endogenous constructs. The magnitude of each β value indicates the relative importance of the predictor, while its statistical significance was assessed through bootstrapped t-values and p-values.

The coefficient of determination (R^2) was used to evaluate the model's explanatory power for each endogenous construct, particularly Behavioural Intention and Actual Use of BL. R^2 values represent the proportion of variance in the dependent variable that is explained by the predictor constructs. In behavioural research, R^2 values of approximately 0.25 are considered weak, 0.50 moderate, and 0.75 substantial (Chin, 2010; Hair et al., 2017). Thus, the R^2 values obtained in this study indicate the extent to which UTAUT2 and TPACK constructs jointly explain BL adoption among academic staff.

Effect size (f^2) was calculated to assess the contribution of each predictor construct to the R^2 value of the endogenous constructs. Effect size analysis complements path coefficients by indicating the practical impact of each predictor. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

Predictive relevance was evaluated using the Stone–Geisser Q^2 statistic, obtained through the blindfolding procedure. A Q^2 value greater than zero indicates that the model has predictive relevance and can accurately predict omitted data points (Stone, 1974; Geisser, 1975; Hair et al., 2017). The presence of positive Q^2 values for the endogenous constructs demonstrates the model's out-of-sample predictive capability, which is a central objective of PLS-SEM.

3.7.1.2 Bootstrapping for Hypothesis Testing

To test the statistical significance of the hypothesised relationships, a bootstrapping procedure with 5,000 resamples was performed. Bootstrapping is a non-parametric technique that does not require normally distributed data and is recommended for hypothesis testing in PLS-SEM (Hair et al., 2017; Henseler et al., 2016).

Bootstrapping generated standard errors, t-values, p-values, and confidence intervals for each path coefficient. A hypothesis was considered supported when the corresponding path coefficient was statistically significant ($p < 0.05$), and the confidence interval did not include zero. These results provide robust evidence for accepting or rejecting the proposed hypotheses and are reported in the subsequent chapter.

3.7.1.3 Summary of Data Analysis Approach

Overall, the PLS-SEM analysis adhered to established methodological standards and ensured a rigorous evaluation of both the measurement and structural models. By assessing reliability, validity, explanatory power, effect sizes, and predictive relevance, the analysis provides a comprehensive understanding of the factors influencing the adoption of BL among academic staff. This approach aligns with the study's objective to integrate acceptance-based and knowledge-based perspectives within a single predictive model.

3.8 Conclusion

This chapter outlines the methodological approach adopted to investigate the adoption of BL among academic staff at UTHM. Grounded in a positivist paradigm, the study employed a quantitative, cross-sectional survey design to examine the relationships proposed in the integrated UTAUT2–TPACK framework.

The chapter explains the development of the research instrument, which was constructed by adapting established and validated measures to ensure conceptual alignment with the underlying theories and contextual suitability for the Malaysian higher education setting. A stratified random sampling strategy was employed to ensure proportional representation across faculties and academic centres, thereby strengthening the generalisability of the findings within the institutional context.

Prior to full-scale data collection, a pilot study was conducted to assess the clarity, reliability, and preliminary validity of the instrument. Feedback from expert reviewers and pilot respondents informed minor refinements, enhancing the instrument's measurement quality. Data were subsequently collected using an online survey and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS. This analytical approach enabled systematic evaluation of the measurement model and testing of the hypothesised structural relationships.

Overall, this chapter establishes a transparent and methodologically rigorous foundation for the study. The following chapter presents the empirical findings derived from the PLS-SEM analysis and evaluates the proposed hypotheses in relation to the integrated conceptual model.

CHAPTER FOUR
FINDINGS

4.0 Introduction

Building upon the theoretical foundations and methodological principles established in the previous chapters, this chapter presents the empirical findings of the study. It focuses on a systematic analysis of the data collected from academic staff across various faculties at UTHM to explore the complexities involved in academic staff's adoption and use of BL.

The chapter begins with a brief overview of the research design, outlining the data analysis procedures guided by the UTAUT2 and TPACK frameworks. Central factors such as PE, EE, and SI are examined to understand their influence on academic staff's behavioural intentions and actual use of BL.

Furthermore, the chapter analyses the hypotheses formulated in Chapter 1 by applying relevant statistical techniques to derive meaningful insights from the survey data. This chapter plays a crucial role in transforming raw data into structured findings, thereby bridging theoretical understanding with practical realities within the Malaysian higher education context.

Throughout this process, the study recognises that data analysis is not merely a quantitative exercise but also a narrative exploration of how technology shapes academic practices in higher education. The results offer valuable contributions to the ongoing scholarly discourse on BL and may provide insights that inform future educational policies and practices.

4.1 Data Collection

4.1.0 Acceptance Rate

The data collection process was conducted over a four-week period, from 1 November 2021 to 23 November 2021. As outlined in Chapter 3, the required sample size for this study was determined using the Krejcie and Morgan (1970) sampling table, which indicated that a minimum of 396 respondents was required based on the study population. To address potential non-response and incomplete questionnaires, an oversampling strategy was employed by distributing an additional 25 questionnaires, resulting in a total of 421 questionnaires distributed across faculties and centres.

The distribution of questionnaires and the number of responses obtained from each faculty and centre are summarised in Table 4.1.

Table 4.1
Respondents and Response Rate

No	Faculty/Centre	Sample Size	Questionnaires Distributed	Questionnaires Returned
1	Faculty of Civil & Environmental Engineering (FKAAB)	25	26	15
2	Faculty of Technical & Vocational Education (FPTV)	24	26	20
3	Faculty of Applied Sciences & Technology (FAST)	28	30	18
4	Faculty of Technology Management & Business (FPTP)	26	28	20
5	Faculty of Electrical & Electronic Engineering (FKEE)	27	29	20
6	Faculty of Computing & Information Technology (FSKTM)	25	27	21
7	Faculty of Engineering Technology (FTK)	25	27	19

No	Faculty/Centre	Sample Size	Questionnaires Distributed	Questionnaires Returned
8	Faculty of Mechanical & Manufacturing Engineering (FKMP)	28	30	23
9	Centre for Language Studies (CLS)	50	52	31
10	Co-curricular Unit	50	52	39
11	Graduate Studies Centre	28	30	25
12	Diploma Studies Centre	30	32	25
13	Continuing Education Centre	30	32	24
	Total	**396**	**421**	**300**
	Response rate 71.9%			

Following the distribution shown in Table 4.1, a total of 300 questionnaires were returned from the 421 distributed, resulting in an overall response rate of 71.9%. This response rate is considered high for online survey research and exceeds commonly reported benchmarks in organisational and educational studies (Baruch & Holtom, 2008; Dillman, Smyth, & Christian, 2014).

Although the final number of returned questionnaires did not reach the initially targeted sample size of 396, the obtained sample of 300 responses is adequate for analysis using PLS-SEM, which is suitable for predictive research models and performs well with moderate sample sizes. In addition, responses were proportionally obtained across faculties and centres, supporting the representativeness of the sample.

Response rates varied across faculties and centres, with the Centre for Language Studies and the Co-curricular Unit recording the highest return rates.

4.1.1 Data Scanning and Initial Analysis

Prior to conducting the main data analysis, data screening was performed to ensure the accuracy, completeness, and suitability of the dataset for further statistical analysis. Data screening is an essential preliminary step as it helps identify potential issues related to missing data, assumption violations, and data quality (Hair et al., 2017). It also enables researchers to gain an initial understanding of the collected data (Hair et al., 2017).

In this study, data screening commenced with the examination of the 300 questionnaires returned. The screening process indicated that all questionnaires were fully completed, and no missing data were detected. As such, all responses were deemed suitable for subsequent analysis.

4.1.2 Outliers

Outliers refer to observations that deviate markedly from other data points in a dataset and may distort statistical results if not appropriately addressed (Pallant, 2016). In this study, multivariate outlier analysis was conducted using the Mahalanobis distance (MD) method via SPSS software, following the recommendations of Tabachnick and Fidell (2007).

Multivariate outliers were identified by comparing the Mahalanobis distance values against a chi-square distribution with degrees of freedom equal to the number of predictor variables, using a significance level of $p < 0.001$. Cases with probability values lower than 0.001 were considered multivariate outliers and were removed from the dataset.

The analysis revealed that two cases exceeded the critical Mahalanobis distance threshold and were therefore identified as multivariate outliers. These cases were subsequently removed from the dataset. As a result, a total of 298 responses remained and were retained for further analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM).

4.1.3 Normality Test

An assessment of data distribution normality was conducted as part of the preliminary data screening process. Although PLS-SEM does not require the assumption of multivariate normality, examining data distribution provides useful descriptive insight into the characteristics of the dataset (Hair et al., 2017).

Normality was assessed using the Kolmogorov–Smirnov test with Lilliefors significance correction and the Shapiro–Wilk test. The results of these tests are presented in Table 4.2.

Table 4.2
Normality Test

Tests of Normality

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Normality	.095	298	.200	.948	298	.358

a. Lilliefors Significance Correction

As shown in Table 4.2, both tests produced significance values greater than the conventional threshold of 0.05, indicating no significant deviation from normality. While normality is not a prerequisite for PLS-SEM analysis, these results suggest that the data distribution does not exhibit severe non-normality, supporting the overall quality and stability of the dataset for subsequent analysis.

4.1.4 Multicollinearity Test

Multicollinearity occurs when two or more predictor variables are highly correlated, which may inflate standard errors and compromise the stability and interpretability of regression estimates (Tabachnick & Fidell, 2007). In the context of structural equation modelling, assessing multicollinearity is crucial to ensure that each construct makes a unique contribution to the model's explanatory power.

In this study, multicollinearity was assessed using the Variance Inflation Factor (VIF) and tolerance values. According to Hair, Ringle, and Sarstedt (2017), multicollinearity is considered problematic when VIF values exceed 5.0 or when tolerance values fall below 0.20. The tolerance and VIF values for all predictor variables are presented in Table 4.3.

Table 4.3
Tolerance Value and Variance Inflation Factor (VIF)

Variable	Collinearity statistics	
	Tolerance	VIF
Performance Expectancy (PE)	.419	2.387
Effort Expectancy (EE)	.389	2.571
Social Influence (SI)	.416	2.405
Facilitating Condition (FC)	.428	2.338
Hedonic Motivation (HM)	.312	3.208
Habit (HT)	.842	1.187
Pedagogical Knowledge (PK)	.421	2.356
Content Knowledge (CK)	.379	2.517
Technological Knowledge (TK)	.411	2.400

As shown in Table 4.3, all VIF values are below the recommended threshold of 5.0, and all tolerance values exceed 0.20. These results indicate that multicollinearity is not a concern in this study, and the predictor constructs can be retained for subsequent PLS-SEM analysis.

4.1.5 Non-response Bias Test

Non-response bias refers to systematic differences between respondents and non-respondents that may affect the representativeness of survey findings. In this study, a formal non-response bias test based on an early–late respondent comparison was not conducted because the questionnaires were collected within a fixed data collection window, and responses were received in a relatively uniform manner, without a clear distinction between early and late submissions.

Nevertheless, the potential impact of non-response bias was addressed through oversampling and by achieving a high overall response rate of 71.9%, which exceeds commonly reported thresholds in organisational and educational survey research (Baruch & Holtom, 2008). Although non-response bias cannot be entirely ruled out, the strong response rate and proportional representation across faculties and centres indicate that the risk of non-response bias in this study is likely to be minimal.

4.1.6 Common Method Variance (CMV) Test

Common Method Variance (CMV) occurs when variance in responses is attributable to the measurement method rather than the constructs being measured, potentially inflating observed relationships (Podsakoff et al., 2003; Spector, 2011). To reduce the likelihood of CMV, several procedural remedies were implemented during the survey design stage, including assuring respondents of confidentiality and anonymity, and using clear, concise, and unambiguous questionnaire items (Baumgartner & Weijters, 2012; Podsakoff, MacKenzie, & Podsakoff, 2012).

In addition to these procedural controls, Harman’s single-factor test was conducted as a post hoc statistical assessment of CMV, following the approach suggested by

Podsakoff and Organ (1986). All measurement items were entered into an unrotated principal components analysis. The results indicated the emergence of seven factors, with the largest factor accounting for 19.088% of the total variance, which is well below the commonly cited threshold of 50%.

These findings suggest that CMV is unlikely to pose a serious threat to the validity of the study results. However, consistent with best practice, CMV cannot be eliminated and is acknowledged as a potential limitation.

4.2 Descriptive Analysis

This section presents the descriptive analysis of the demographic characteristics of the respondents involved in the study. The analysis focuses on key demographic variables, including gender, age, and teaching experience, to provide an overview of the academic staff profile at UTHM.

4.2.1 Demographic Profile

The demographic profile of the respondents provides an overview of the characteristics of the academic staff who participated in the survey. The respondents were categorised based on gender, age, and years of teaching experience. Age was grouped into three categories: under 35 years, 36-50 years, and above 50 years. Teaching experience was also classified into three groups: below 5 years, 6–15 years, and more than 15 years. These categories were used to facilitate descriptive comparison across respondent groups.

The distribution of respondents according to gender, age, and teaching experience is summarised in Table 4.4. Following data screening and outlier removal, a total of 298 respondents were included in the analysis.

Table 4.4
Demographic Characteristics of Respondents (n = 298)

Variable	**Count**	**Percentage (%)**
Gender		
Male	134	45.0
Female	164	55.0
Age Range		
Under 35	105	35.2
36-50	109	36.6
Above 50	84	28.2
Working Experience		
Below 5 years	60	20.1
6-15 years	148	49.7
More than 15 years	90	30.2
Total Respondents	298	100.00

As shown in Table 4.4, female respondents constituted a slightly larger proportion of the sample (55.0%) compared to male respondents (45.0%). In terms of age, respondents were relatively evenly distributed across the under-35 and 36-50 age groups, while a smaller proportion was represented by respondents above the age of 50. Regarding teaching experience, nearly half of the respondents reported having between 6 and 15 years of experience, followed by those with more than 15 years of experience. Respondents with less than 5 years of experience formed the smallest group.

4.2.2 Variables Descriptive Analysis

This section presents the descriptive statistics for the key constructs examined in the study. Descriptive analysis was conducted to summarise the central tendency and variability of the measured variables prior to measurement and structural model assessment. Following data screening and outlier removal, a total of 298 responses were included in the analysis.

The constructs analysed include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Pedagogical Knowledge (PK), Content Knowledge (CK), Technological Knowledge (TK), Behavioural Intention (BI), and Actual Use (AU). Each construct was measured using between three and seven items. The descriptive statistics for all constructs are summarised in Table 4.5.

Table 4.5
Summary of Variables' Descriptive Analysis

Variable	Total items	Mean	Standard deviation (SD)
Performance Expectancy (PE)	4	5.41	0.817
Effort Expectancy (EE)	4	5.27	0.872
Social Influence (SI)	4	5.45	0.798
Facilitating Conditions (FC)	3	5.60	0.664
Hedonic Motivation (HM)	3	5.47	0.769
Habit (HT)	3	5.41	0.989
Pedagogical Knowledge (PK)	7	5.22	0.902
Content Knowledge (CK)	5	5.06	0.879
Technological Knowledge (TK)	4	5.27	0.849
Behavioural Intention (BI)	3	4.64	0.824
Actual Use (AU)	3	5.27	0.919

The results in Table 4.5 indicate that mean scores across the constructs ranged from 4.64 to 5.60, suggesting generally positive responses on the Likert scale. The standard deviation values, which ranged from 0.664 to 0.989, indicate moderate variability in responses across all constructs.

4.3 Inferential Analysis

Inferential analysis in this study was conducted using PLS-SEM, implemented with the aid of the SmartPLS software. PLS-SEM analysis involves two main stages: (i) measurement model assessment and (ii) structural model assessment, which are evaluated sequentially to ensure the reliability and validity of the proposed research model (Hair et al., 2017; Henseler et al., 2009). Figure 4.1 presents an overview of the PLS-SEM model assessment procedure adopted in this study.

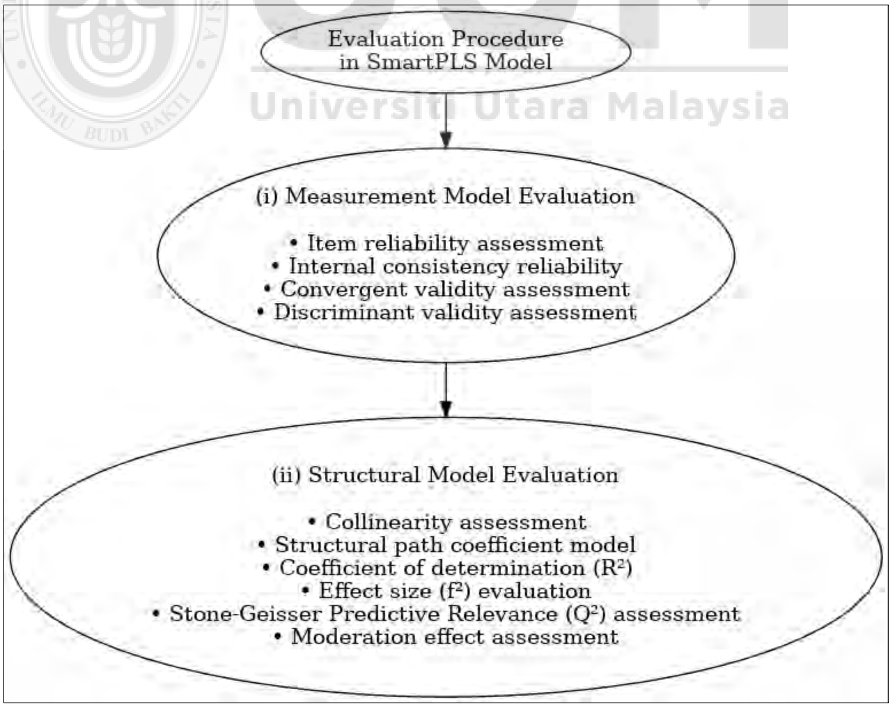

Figure 4.1 Summary of PLS-SEM Model Assessment Procedure
Source: Henseler et al. (2009).

As illustrated in Figure 4.1, the model evaluation process begins with the measurement model assessment, which examines item reliability, internal consistency reliability, convergent validity, and discriminant validity. Once the measurement model meets the recommended criteria, the analysis proceeds to the structural model assessment, which includes the evaluation of collinearity, path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and moderation effects.

This sequential evaluation ensures that the measurement properties of the constructs are established prior to testing the hypothesised relationships within the structural model, thereby enhancing the robustness and interpretability of the inferential findings.

4.3.1 Measurement Model Assessment

The measurement model in this study is specified as a reflective measurement model, as the observed indicators are assumed to be manifestations of their underlying latent constructs. In accordance with established guidelines for PLS-SEM, the assessment of the reflective measurement model was conducted through three main evaluation procedures (Chin, 2010; Hair et al., 2017).

First, internal consistency reliability was assessed to determine the reliability of each construct. This was evaluated using Cronbach's alpha and composite reliability (CR) values to ensure that the indicators consistently measure the same underlying construct.

Second, convergent validity was examined to assess the extent to which indicators of a construct converge or share a high proportion of variance. Convergent validity was evaluated using the average variance extracted (AVE) and outer loading values, as recommended by Hair et al. (2017).

Third, discriminant validity was assessed to ensure that each construct is empirically distinct from other constructs in the model. Discriminant validity was evaluated using three criteria: (a) cross-loading analysis, (b) the Fornell–Larcker criterion, and (c) the Heterotrait–Monotrait (HTMT) ratio, in line with current best practices in PLS-SEM (Hair et al., 2017).

4.3.1.0 Reliability and Convergent Validity

The reliability and convergent validity of the reflective measurement model were assessed using the PLS algorithm, following the guidelines proposed by Hair et al. (2017). Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR), while convergent validity was assessed using indicator (outer) loadings and the average variance extracted (AVE).

During the initial assessment, several indicators exhibited outer loading values below the recommended threshold of 0.70. In line with established PLS-SEM guidelines, indicators with low outer loadings were examined and removed where their exclusion contributed to improvements in construct reliability and convergent validity (Vinzi et al., 2010; Hair et al., 2017). Accordingly, eight indicators were removed from the measurement model: AU2, BI3, PE4, EE1, HT1, PK1, PK2, and TK1. Following the removal of these indicators, the PLS algorithm was re-run to reassess the measurement properties of the model.

The results of the revised measurement model indicate that all constructs achieved satisfactory internal consistency reliability. Cronbach's alpha values were close to or exceeded the recommended threshold of 0.70 (Robinson, Shaver, & Wrightsman, 1991), while composite reliability values also surpassed the minimum acceptable level of 0.70, as suggested by Hair et al. (2017). These findings confirm that the constructs demonstrate adequate internal consistency.

Convergent validity was subsequently assessed by examining the outer loadings and AVE values. All retained indicators exhibited acceptable to strong outer loading values, and all constructs achieved AVE values greater than 0.50, indicating that the constructs explain more than half of the variance of their respective indicators (Hair et al., 2017). Collectively, these results provide evidence that the measurement model satisfies the criteria for both reliability and convergent validity. The detailed reliability and convergent validity results are presented in Table 4.6.

Table 4.6
Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Convergent Validity Values

Construct	Items	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE	Convergent Validity AVE > 0.5
Performance Expectancy	PE1	0.975	0.892	0.927	0.757	YES
	PE2	0.802				
	PE3	0.823				
Effort Expectancy	EE2	0.684	0.748	0.851	0.658	YES
	EE3	0.863				
	EE4	0.873				
Social Influence	SI1	0.884	0.911	0.941	0.842	YES
	SI2	0.941				
	SI3	0.926				
Facilitating Conditions	FC1	0.866	0.847	0.907	0.765	YES
	FC2	0.884				

	FC3	0.873				
Hedonic Motivation	HM1	0.905	0.845	0.895	0.743	YES
	HM2	0.955				
	HM3	0.704				
Habit	HT2	0.788	0.692	0.857	0.751	YES
	HT3	0.939				
Pedagogical Knowledge for Conducting BL	PK3	0.776	0.897	0.927	0.760	YES
	PK4	0.862				
	PK5	0.910				
	PK6	0.932				
Content Knowledge for Conducting BL	CK1	0.908	0.952	0.963	0.838	YES
	CK2	0.949				
	CK3	0.892				
	CK4	0.903				
	CK5	0.924				
Technological Knowledge for Conducting BL	TK2	0.807	0.617	0.837	0.720	YES
	TK3	0.888				
Behavioural Intention	BI1	0.977	0.950	0.976	0.953	YES
	BI2	0.975				
Actual Use	AU1	0.825	0.701	0.866	0.765	YES
	AU3	0.921				

Table 4.6 presents the results of internal consistency reliability and convergent validity for all constructs in the measurement model. The findings indicate that composite reliability values for all constructs exceeded the recommended threshold of 0.70, while average variance extracted (AVE) values were above 0.50. These results provide evidence that the constructs demonstrate adequate internal consistency, reliability, and convergent validity.

4.3.1.1 Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion, which compares the square root of the average variance extracted (AVE) of each construct with its correlations with other constructs (Fornell & Larcker, 1981; Hair et al., 2017). As shown in Table 4.7, the square root of AVE values (diagonal elements) for each construct is greater than the corresponding inter-construct correlation values.

These results provide evidence that discriminant validity is established for the measurement model based on the Fornell–Larcker criterion.

Table 4.7
Fornell-Larcker Criterion

	AU	BI	CK	EE	FC	HM	HT	PE	PK	SI	TK
AU	0.874										
BI	-0.122	**0.976**									
CK	-0.076	0.735	**0.915**								
EE	0.017	-0.341	-0.232	**0.811**							
FC	-0.091	0.086	0.093	0.045	**0.875**						
HM	-0.060	0.101	0.119	0.039	0.609	**0.862**					
HT	-0.102	-0.324	-0.295	0.292	0.043	0.130	**0.867**				
PE	0.128	-0.033	-0.006	0.049	0.003	0.045	0.021	**0.870**			
PK	-0.151	0.344	0.482	-0.149	0.084	0.197	0.085	0.031	**0.872**		
SI	-0.048	0.172	0.141	-0.104	-0.076	-0.013	-0.118	0.191	0.038	**0.917**	
TK	0.792	-0.098	-0.069	-0.016	-0.046	-0.049	-0.021	0.103	-0.095	-0.014	**0.849**

Note. AU = Actual Use, BI = Behavioural Intention, CK = Content Knowledge, EE = Effort Expectancy, FC = Facilitating Conditions, HM = Hedonic Motivation, HT = Habit, PE = Performance Expectancy, PK = Pedagogical Knowledge, SI = Social Influence, TK = Technological Knowledge

4.3.1.2 Summary of Measurement Model Evaluation

The summary of the measurement model evaluation is shown in Figure 4.2 below.

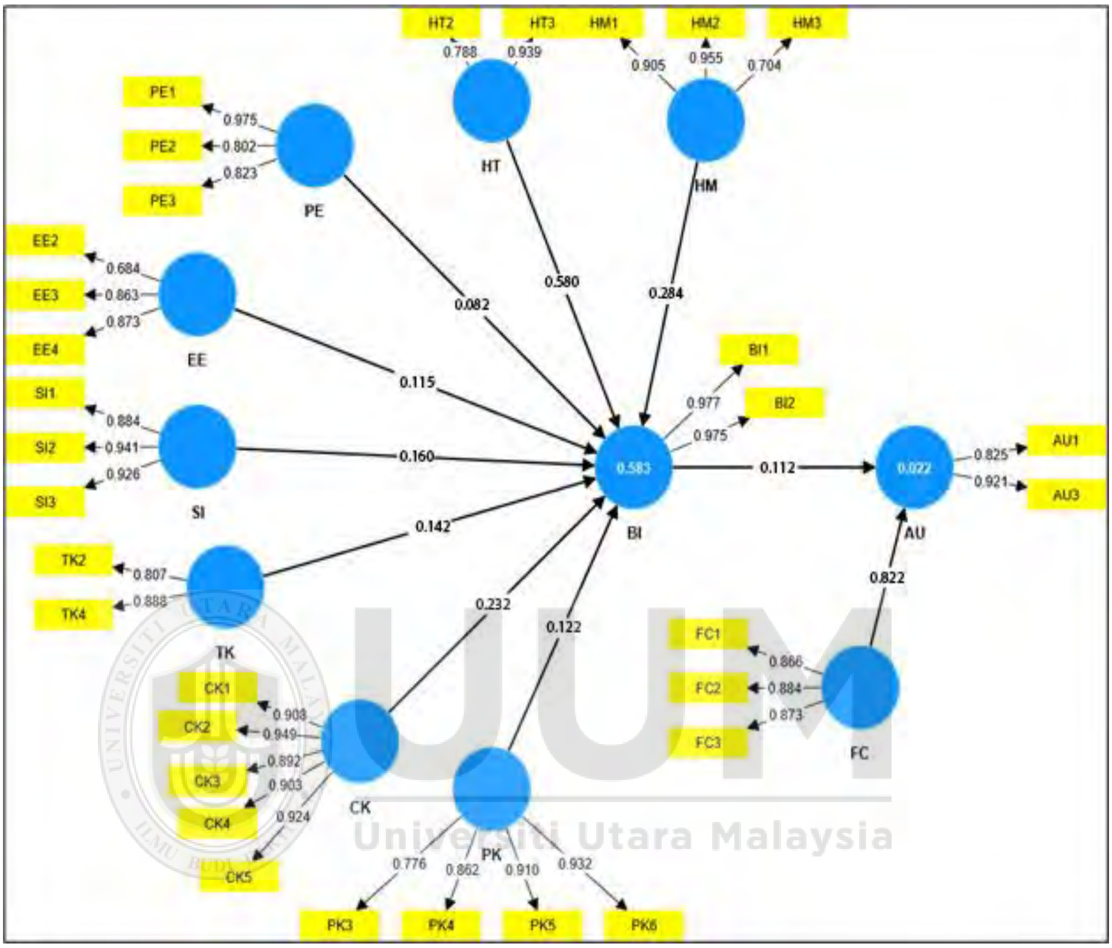

Figure 4.2 Measurement Model Assessment

4.3.2 Structural Model Evaluation

Following the assessment of the measurement model, the second stage of the PLS-SEM analysis involved evaluating the structural model. This stage focuses on examining the hypothesised relationships among constructs and determining the significance of each hypothesis proposed in Chapter 1.

Structural model evaluation was conducted using a bootstrapping procedure with 5,000 subsamples, a one-tailed test, and a significance level of 0.05, in accordance with the recommendations of Hair et al. (2017). Prior to hypothesis testing, collinearity among the predictor constructs was assessed to ensure the stability and interpretability of the estimated path coefficients.

4.3.2.0 Assessment of Collinearity in the Structural Model

Collinearity in the structural model was assessed using the Variance Inflation Factor (VIF) values obtained from the PLS algorithm in the SmartPLS software. Assessing collinearity is essential to ensure that predictor constructs do not exhibit excessive redundancy, which could bias the estimation of structural relationships.

The results of the collinearity assessment are presented in Table 4.8. All VIF values were below the conservative threshold of 3.3, as suggested by Diamantopoulos and Siguaw (2006), indicating that collinearity is not a concern in the structural model. Therefore, the data were deemed suitable for subsequent hypothesis testing.

Table 4.8
Structural Model Collinearity Assessment

Construct	VIF
BI → AU	1.007
CK → BI	1.566
EE → BI	1.149
FC → AU	1.007
HM → BI	1.066
HT → BI	1.293
PE → BI	1.061
PK → BI	1.457
SI → BI	1.075
TK → BI	1.025

4.3.2.1 Path Analysis Evaluation

Path analysis was conducted to examine the direct relationships among the constructs in the structural model and to test the proposed hypotheses. The significance of the hypothesised paths was assessed using a bootstrapping procedure with 5,000 subsamples, employing a one-tailed test at a 0.05 significance level, in line with PLS-SEM guidelines (Hair et al., 2017; Henseler et al., 2009).

In addition to direct effects, path analysis in PLS-SEM also allows for the examination of moderating effects within the structural model (Imam & Hengky, 2015; Hair et al., 2017).

The results of the direct effects analysis for the ten hypothesised relationships are presented in Table 4.9.

Table 4.9
Results of Structural Model Evaluation (Direct Effects)

No.	Hypothesis	Original Sample (β)	p-values	Results
H1	PE → BI	0.082	$p < 0.001$	Significant
H2	EE → BI	0.115	$p < 0.001$	Significant
H3	SI → BI	0.160	$p < 0.001$	Significant
H4	FC → BI	0.822	$p < 0.001$	Significant
H5	HM → BI	0.284	$p < 0.001$	Significant
H6	HT →BI	0.580	$p < 0.05$	Significant
H7	PK →BI	0.122	$p < 0.001$	Significant
H8	CK → BI	0.232	$p < 0.001$	Significant
H9	TK →BI	0.142	$p < 0.001$	Significant
H10	BI →AU	0.112	$p < 0.05$	Significant

The structural model analysis revealed significant relationships between the predictor constructs and Behavioural Intention (BI), as well as between BI and Actual Use (AU).

Performance Expectancy (PE) demonstrated a small but statistically significant positive effect on BI ($\beta = 0.082$, $p < 0.001$), while Effort Expectancy (EE) also showed a significant effect ($\beta = 0.115$, $p < 0.001$). Social Influence (SI) had a significant impact on BI ($\beta = 0.160$, $p < 0.001$), underscoring the role of social factors in the adoption of technology.

Facilitating Conditions (FC) emerged as the strongest predictor of BI, exhibiting a large and significant effect ($\beta = 0.822$, $p < 0.001$), indicating that supportive conditions enhance educators' intention to use BL. Hedonic Motivation (HM) and Habit (HT) were also found to significantly affect BI ($\beta = 0.284$, $p < 0.001$; $\beta = 0.580$, $p < 0.05$, respectively), underscoring the influence of enjoyment and habitual behaviour on actual use intention.

In addition, the knowledge-related constructs, Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK) were significant predictors of BI ($\beta = 0.122$, $p < 0.001$; $\beta = 0.232$, $p < 0.001$; $\beta = 0.142$, $p < 0.001$, respectively), indicating that educators' knowledge competencies contribute positively to their intention to adopt BL. Finally, Behavioural Intention (BI) was found to significantly predict Actual Use (AU) ($\beta = 0.112$, $p < 0.05$), confirming that intention plays a key role in translating acceptance into actual use.

Figure 4.3 presents the structural model results obtained from the PLS-SEM analysis, illustrating the direct relationships between the exogenous constructs and Behavioural Intention (BI), as well as the relationship between BI and Actual Use (AU). The observed indicators are represented by yellow rectangles, while the latent constructs are represented by blue circles. Performance Expectancy (PE), Effort Expectancy

(EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK) were hypothesised to influence BI, which in turn was hypothesised to influence AU. The figure provides a graphical summary of the overall structural model evaluation.

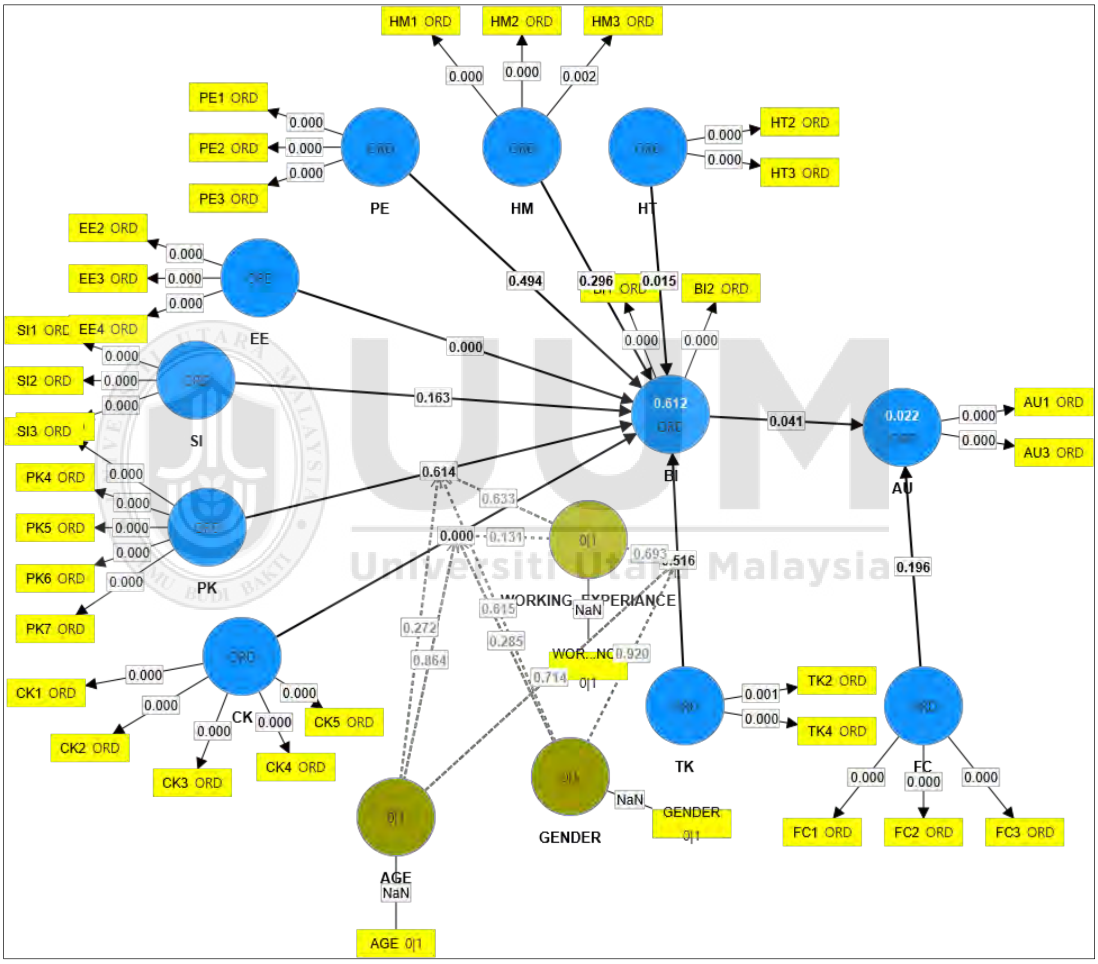

Figure 4.3 Overall Structural Model Assessment

In addition to the direct effects, Hypothesis 11 (H11) was tested to examine the moderating effects of gender, age, and working experience on the relationships between the TPACK-related variables, Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), and Behavioural Intention

(BI). To facilitate detailed analysis, H11 was decomposed into nine sub-hypotheses (H11a–H11i). The results of the moderation analysis are presented in Table 4.10.

Table 4.10 presents the results of the moderation analysis examining the effects of gender, age, and working experience on the relationships between the TPACK-related knowledge constructs, Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), and Behavioural Intention (BI). The moderation effects were assessed using a bootstrapping procedure within the PLS-SEM framework.

Table 4.10
Structural Model Assessment Results (Moderating Effects) – Gender, Age and Working Experience

No	Hypothesis	Original Sample (ß)	Standard Deviation	t-values	p-values	Results
H11a	Moderator effect (Gender) CK → BI	0.129	0.121	1.070	0.285	Not Significant
H11b	Moderator effect (Gender) PK → BI	0.057	0.114	0.503	0.615	Not Significant
H11c	Moderator effect (Gender) TK → BI	0.009	0.087	0.100	0.920	Not Significant
H11d	Moderator effect (Age) CK → BI	0.018	0.108	0.171	0.864	Not Significant
H11e	Moderator effect (Age) PK → BI	0.128	0.117	1.098	0.272	Not Significant
H11f	Moderator effect (Age) TK → BI	0.030	0.081	0.366	0.002	Significant
H11g	Moderator effect (Experience) CK → BI	0.189	0.125	1.508	0.131	Not Significant
H11h	Moderator effect (Experience) PK → BI	0.056	0.117	0.478	0.633	Not Significant

H11i	Moderator effect (Experience) TK → BI	0.032	0.080	0.395	0.003	Significant

Note. AU = Actual Use, BI = Behavioural Intention, CK = Content Knowledge, EE = Effort Expectancy, FC = Facilitating Conditions, HM = Hedonic Motivation, HT = Habit, PE = Performance Expectancy, PK = Pedagogical Knowledge, SI = Social Influence, TK = Technological Knowledge

The results indicate that gender does not moderate the relationships between CK, PK, and TK and Behavioural Intention (BI). Similarly, age does not moderate the effects of CK and PK on BI, nor does teaching experience moderate the effects of CK and PK on BI.

However, age and teaching experience were found to significantly moderate the relationship between Technological Knowledge (TK) and Behavioural Intention (BI), supporting hypotheses H11f and H11i. These findings suggest that the influence of technological knowledge on behavioural intention varies across different age groups and levels of teaching experience.

4.3.3 Structural Model Quality Assessment

This section evaluates the overall quality of the structural model by examining its explanatory power, effect sizes, and predictive relevance, in accordance with established PLS-SEM guidelines (Hair et al., 2017).

4.3.3.0 Assessment of the Coefficient of Determination (R^2)

The coefficient of determination (R^2) is a primary criterion for evaluating the explanatory power of the structural model in PLS-SEM (Hair et al., 2017; Henseler et al., 2009). The R^2 value indicates the proportion of variance in an endogenous construct that is explained by its predictor variables.

The R^2 values for the endogenous constructs in this study, Behavioural Intention (BI) and Actual Use (AU), are presented in Table 4.11.

Table 4.11
Coefficient of Determination R^2

Endogenous Variable	R^2
Behavioural Intention	0.612
Actual Use	0.022

As shown in Table 4.11, the R^2 value for Behavioural Intention (BI) is 0.612, indicating that the predictors in the model explain a substantial proportion of the variance in BI. In contrast, the R^2 value for Actual Use (AU) is 0.022, suggesting that the model explains only a small proportion of the variance in actual use behaviour.

4.3.3.1 Assessment of Effect Size (f^2)

In addition to R^2, effect size (f^2) was examined to assess the contribution of each exogenous construct to the R^2 value of the endogenous constructs. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The effect size results are presented in Table 4.12.

Table 4.12
Assessment of Effect Size, f^2

Variable	Behavioural Intention (BI)	AU
Performance Expectancy (PE)	0.002	
Effort Expectancy (EE)	0.058	
Social Influence (SI)	0.007	
Facilitating Conditions (FC)	0.002	0.007
Hedonic Motivation (HM)	0.001	

Habit (HT)	0.002	
Pedagogical Knowledge (PK)	0.000	
Content Knowledge (CK)	0.383	
Technological Knowledge (TK)	0.017	
Behavioural Intention (BI)		0.013

The results indicate that Content Knowledge (CK) exhibits a large effect size on Behavioural Intention ($f^2 = 0.383$), while all other predictors demonstrate small to negligible effects on BI. For Actual Use (AU), Behavioural Intention shows a small effect size ($f^2 = 0.013$), and Facilitating Conditions exhibit a negligible effect ($f^2 = 0.007$).

4.3.3.2 Predictive Relevance Test (Q^2)

Predictive relevance of the structural model was assessed using the Stone–Geisser Q^2 statistic obtained through the blindfolding procedure. The Q^2 value evaluates the model's capability to predict observed values of endogenous constructs, where values greater than zero indicate that the model has predictive relevance (Hair et al., 2017). Additionally, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were examined as supplementary indicators of predictive accuracy, with lower values indicating better predictive performance. The predictive relevance results for the endogenous constructs, Behavioural Intention (BI) and Actual Use (AU), are presented in Table 4.13.

Table 4.13
Latent Variable (LV) Prediction Summary

	Q^2predict	**RMSE**	**MAE**
AU	0.011	0.999	0.816
BI	0.545	0.680	0.511

As shown in Table 4.13, the Q^2predict value for Behavioural Intention (BI) is 0.545, indicating that the model demonstrates substantial predictive relevance for BI. In contrast, the Q^2predict value for Actual Use (AU) is 0.011, suggesting minimal predictive relevance for this construct. Consistent with the Q^2 results, BI exhibits lower RMSE and MAE values compared to AU, indicating relatively better predictive accuracy for Behavioural Intention.

4.3.3.3 Assessment of the Moderator Effectiveness

The effectiveness of the moderating variables in this study was assessed using the product indicator approach within the PLS-SEM framework. This approach was employed to estimate the moderating effects of age, gender, and working experience on the relationships between the TPACK-related knowledge constructs, Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), and Behavioural Intention (BI).

To evaluate the magnitude of the moderating effects, effect size (f^2) values were examined in accordance with the criteria proposed by Cohen (1988), where values of 0.02, 0.15, and 0.35 indicate small, medium, and large moderating effects, respectively.

Hypotheses H11a to H11i were formulated to test whether age, gender, and working experience moderate the relationships between CK, PK, TK, and BI. The results of these moderation analyses, including the significance and effect sizes of the interaction terms, are reported in Table 4.10.

4.3.4 Moderation Analysis

This section examines the moderating effects of selected demographic variables on the relationships between TPACK-related knowledge constructs and Behavioural Intention, as specified in the research hypotheses.

4.3.4.0 Assessment of the Moderator Effectiveness

The effectiveness of the proposed moderating variables was evaluated using interaction effects estimated within the PLS-SEM framework, following established procedures for moderation analysis (Hair et al., 2017).

4.3.4.1 Gender Effect

Figures 4.4, 4.5, and 4.6 show simple slope analysis graphs that investigate the interaction effect of Gender on the relationship between Content Knowledge (CK), Pedagogical Knowledge (PK), Technological Knowledge (TK), and Behavioural Intention (BI). The graphs display two lines representing the slopes of the relationships between the knowledge constructs and BI for two groups differentiated by Gender: one group coded as 0 (male) and another coded as 1 (female), assuming a binary gender classification.

Figure 4.4 illustrates positive slopes for both gender groups, indicating that Content Knowledge (CK) is positively associated with Behavioural Intention (BI) for both males and females. Although the slope for the female group appears slightly steeper than that of the male group, this visual difference should be interpreted with caution.

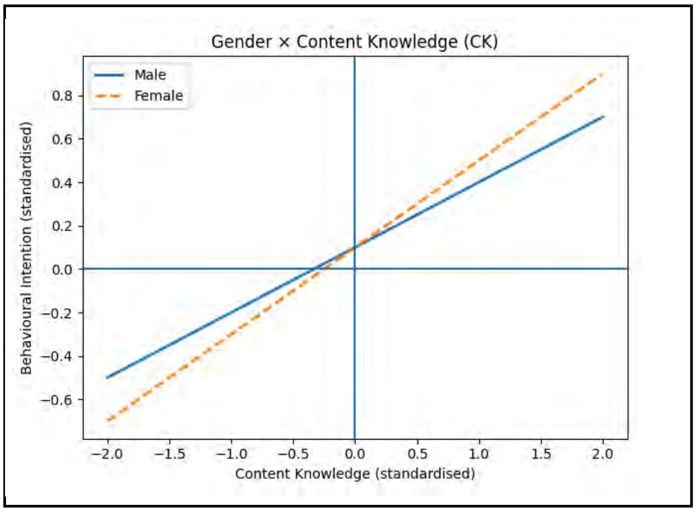

Figure 4.4 Interaction between Gender and Content Knowledge (CK)

Consistent with the moderation analysis results reported in Table 4.10, the interaction effect between Gender and CK on BI was not statistically significant. Therefore, while the figure suggests broadly similar positive relationships across gender groups, Gender does not statistically moderate the relationship between CK and BI.

Figure 4.5 illustrates a positive slope for the male group, indicating that higher levels of Pedagogical Knowledge (PK) are associated with higher Behavioural Intention (BI) among male academic staff members.

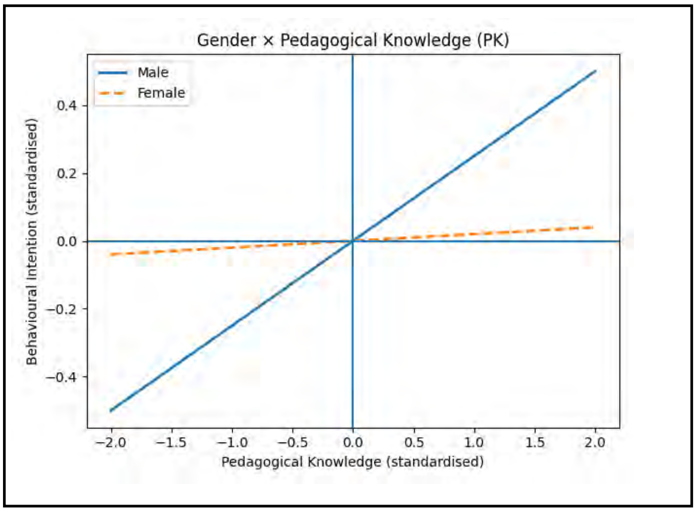

Figure 4.5 Interaction between Gender and Pedagogical Knowledge (PK)

In contrast, the slope for the female group appears relatively flat, suggesting little change in BI as PK increases. Although a visual difference between the slopes can be observed, the moderation analysis results reported in Table 4.10 indicate that the interaction effect between Gender and PK on BI is not statistically significant. Therefore, the observed pattern should be interpreted descriptively rather than inferentially, and Gender does not moderate the relationship between PK and BI in this study.

The analysis does not support a statistically significant moderating effect of Gender on the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI). Although the simple slope plot suggests that PK is positively associated with BI for the male group, the relationship appears weaker for the female group; however, the interaction term between Gender and PK was not statistically significant. Therefore, the observed difference in slopes should be interpreted descriptively rather than as evidence of moderation.

Figure 4.6 presents a simple slope analysis illustrating the interaction between Gender and Technological Knowledge (TK) on Behavioural Intention (BI).

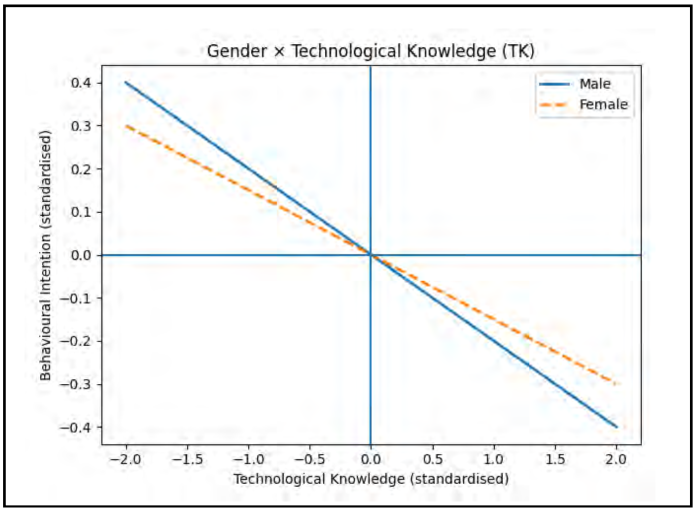

Figure 4.6 Interaction between Gender and Technological Knowledge (TK)

The figure shows a negative slope for the male group and a relatively flat slope for the female group, indicating differing directional patterns between the two gender groups. However, consistent with the moderation analysis results reported in Table 4.10, the interaction effect between Gender and TK on BI was not statistically significant. As such, Gender does not moderate the relationship between TK and BI, and the visual patterns observed should not be interpreted as causal or inferential effects.

Overall, the moderation analyses indicate that Gender does not exert a statistically significant moderating effect on the relationships between the examined knowledge components (PK and TK) and Behavioural Intention. Although minor variations in slope direction and magnitude were observed across gender groups, these differences were not supported by significant interaction effects and therefore do not warrant inferential interpretation. Accordingly, Gender was not found to be a meaningful moderating variable in explaining behavioural intention towards BL adoption in this study. The subsequent section extends the moderation analysis by examining the role of age, a demographic factor that is theoretically and empirically more closely associated with variations in technological competence and adoption behaviour.

4.3.4.2 Age effect

Figures 4.7, 4.8, and 4.9 present simple slope plots illustrating the interaction between **Age** and Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) on Behavioural Intention (BI), where Age = 0 represents respondents below 35 years and Age = 1 represents respondents aged 35 years and above.

Figure 4.7 illustrates the interaction between Age and Content Knowledge (CK) on Behavioural Intention (BI).

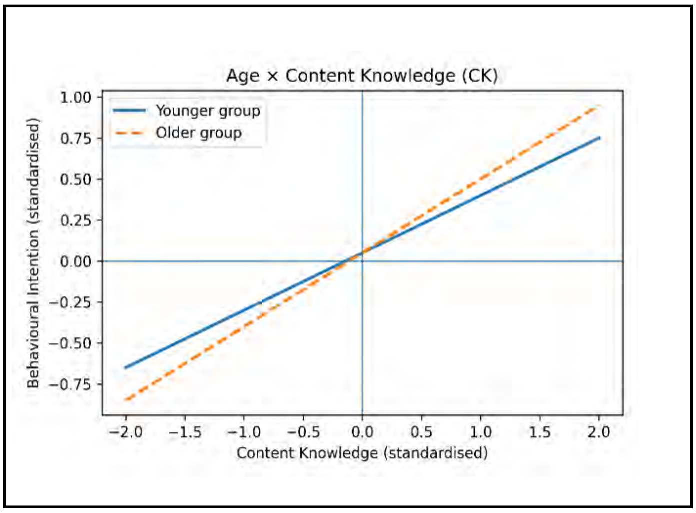

Figure 4.7 Interaction between Age and Content Knowledge (CK)

Both age groups show positive slopes, indicating that higher levels of CK are associated with higher BI regardless of age group. Although the slope for the older age group appears steeper than that of the younger group, the moderation analysis reported in Table 4.10 indicates that the interaction effect between Age and CK on BI is not statistically significant. Therefore, the observed difference in slopes should be interpreted descriptively, and Age does not moderate the relationship between CK and BI in a statistically meaningful way.

Figure 4.8 presents a simple slope analysis illustrating the interaction between Age and Pedagogical Knowledge (PK) on Behavioural Intention (BI). The slope for the younger age group (Age at 0) is positive, indicating that higher levels of PK are associated with higher BI among younger academic staff. In contrast, the slope for the older age group (Age at 1) appears relatively flat, suggesting minimal change in BI as PK increases.

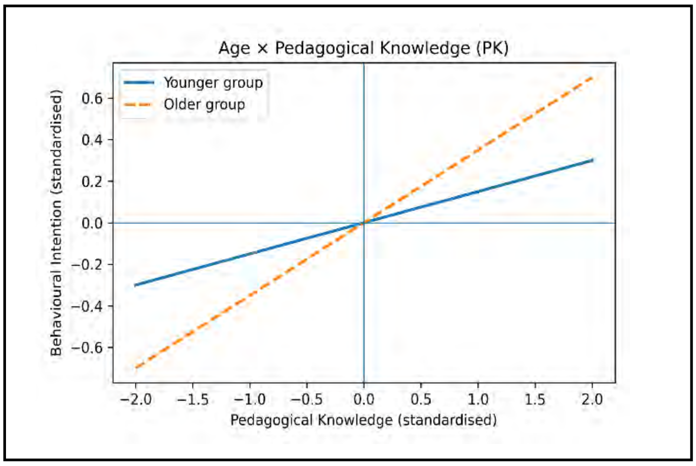

Figure 4.8 Interaction between Age and Pedagogical Knowledge (PK)

Although a visual difference in slope patterns can be observed between the two age groups, the moderation analysis results reported in Table 4.10 indicate that the interaction effect between Age and PK on BI is not statistically significant. Therefore, Age does not moderate the relationship between PK and BI, and the observed pattern should be interpreted descriptively rather than as evidence of a moderating effect.

Figure 4.9 presents a simple slope analysis illustrating the interaction between Age and Technological Knowledge (TK) on Behavioural Intention (BI).

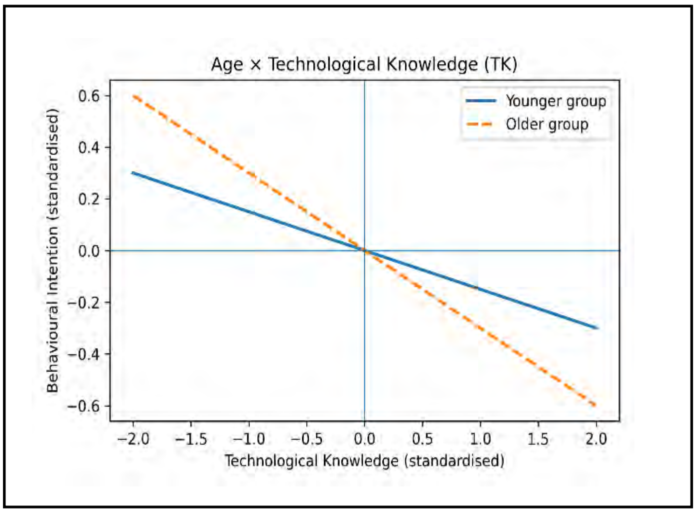

Figure 4.9 Interaction between Age and Technological Knowledge (TK)

Consistent with the moderation analysis results reported in Table 4.10, the interaction effect between Age and TK on BI is statistically significant, indicating that Age moderates the relationship between Technological Knowledge and Behavioural Intention. This finding demonstrates that the influence of TK on BI varies across age groups, with a stronger negative effect observed among older respondents.

While age provides insights into generational differences in technological exposure and adaptation, it does not fully capture the extent of academic staff's professional trajectories within higher education. Teaching experience represents a distinct demographic dimension, reflecting accumulated instructional practice, pedagogical routines, and prolonged engagement with institutional systems. As such, experience may influence how technological knowledge is translated into behavioural intention independently of chronological age. The following section, therefore, examines the moderating effect of teaching experience on the relationship between knowledge components and behavioural intention towards BL adoption.

4.3.4.3 Teaching Experience Effect

Figures 4.10, 4.11, and 4.12 present simple slope plots illustrating the interaction between Teaching Experience and Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) on Behavioural Intention (BI). The plots depict two groups based on the binary coding of teaching experience, where Teaching Experience is coded as 0 (less than 15 years) and as 1 (more than 15 years).

Figure 4.10 illustrates the interaction between Teaching Experience and Content Knowledge (CK) on Behavioural Intention (BI). Both experience groups show positive slopes, indicating that higher levels of CK are associated with higher BI regardless of teaching experience. Although the slope for the higher experience group appears steeper, the moderation analysis results reported in Table 4.10 indicate that the interaction effect between Teaching Experience and CK on BI is not statistically significant. Therefore, Teaching Experience does not moderate the relationship between CK and BI, and the observed difference in slopes should be interpreted descriptively.

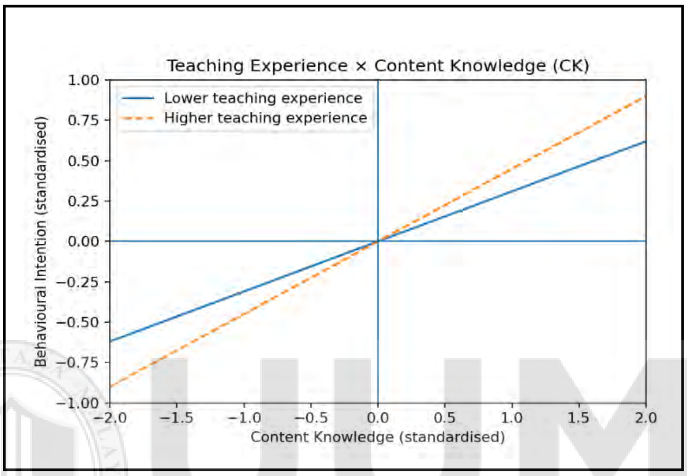

Figure 4.10 Interaction between Teaching Experience and Content Knowledge (CK)

Figure 4.11 presents a simple slope analysis illustrating the interaction between Teaching Experience and Pedagogical Knowledge (PK) on Behavioural Intention (BI). The slope for the lower experience group (Teaching Experience at 0) is positive, indicating that higher levels of PK are associated with higher BI among academic staff with less than 15 years of experience. In contrast, the slope for the higher experience group (Teaching Experience at 1) appears relatively flat, suggesting minimal change in BI as PK increases for this group.

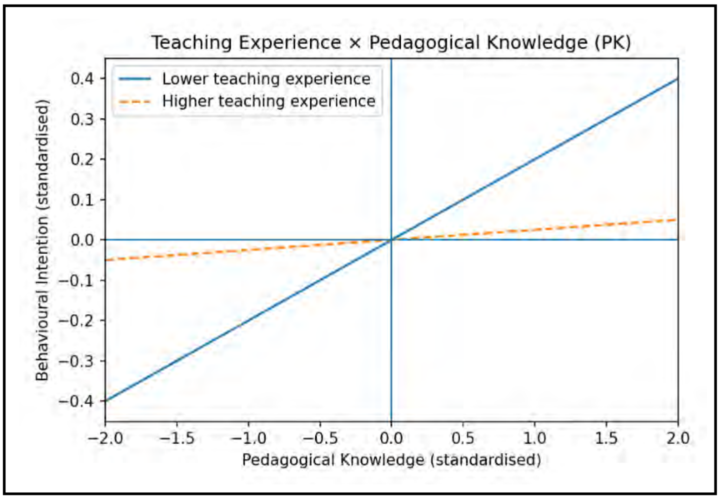

Figure 4.11 Interaction between Teaching Experience and Pedagogical Knowledge (PK)

Although a visual difference in slope patterns can be observed between the two experience groups, the moderation analysis results reported in Table 4.10 indicate that the interaction effect between Teaching Experience and PK on BI is not statistically significant. Therefore, Teaching Experience does not moderate the relationship between PK and BI, and the observed pattern should be interpreted descriptively rather than as evidence of a moderating effect.

Figure 4.12 presents a simple slope analysis illustrating the interaction between Teaching Experience and Technological Knowledge (TK) on Behavioural Intention (BI). The slope for the lower experience group (Teaching Experience at 0) is negative, indicating that higher levels of TK are associated with lower BI among academic staff with less than 15 years of experience. In contrast, the slope for the higher experience group (Teaching Experience at 1) appears relatively flat, suggesting minimal change in BI as TK increases for more experienced academic staff.

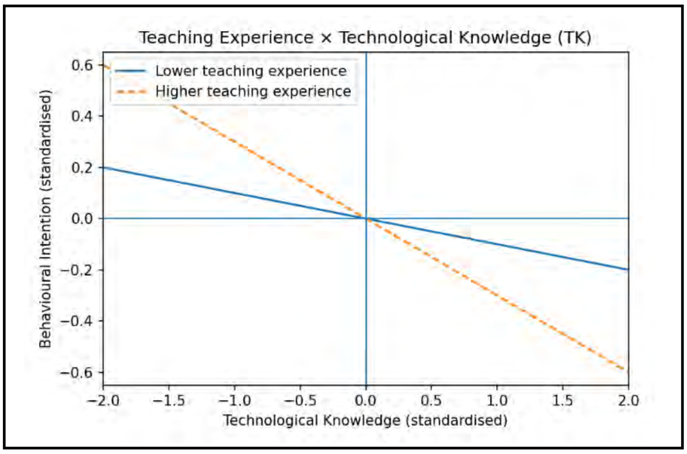

Figure 4.12 Interaction between Teaching Experience and Technological Knowledge (TK)

Consistent with the moderation analysis results reported in Table 4.10, the interaction effect between Teaching Experience and TK on BI is statistically significant, indicating that Teaching Experience moderates the relationship between Technological Knowledge and Behavioural Intention. This finding demonstrates that the influence of TK on BI differs across experience levels, with a stronger negative effect observed among less experienced respondents.

In summary, the moderation analyses demonstrate that demographic effects in this study are not uniform across variables, with Age and Teaching Experience influencing the relationship between TK and BI in distinct ways. While Gender did not exhibit a significant moderating role, both Age and Teaching Experience contributed meaningful explanatory insights into variations in BL adoption among academic staff. Having examined the direct effects and moderation effects in detail, the following section synthesises the key findings of the structural model assessment and highlights the overall explanatory power and predictive relevance of the proposed research model.

4.4 Summary of Structural Model Assessment Findings

Table 4.14 summarises the results of the structural model assessment, presenting the hypotheses tested (H1–H11i), their statistical significance, and the corresponding decisions.

For the direct effects (H1–H10), all hypothesised relationships were found to be statistically significant. Specifically, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK) significantly influenced Behavioural Intention (BI), while BI significantly predicted Actual Use (AU). Accordingly, all direct-effect hypotheses (H1–H10) were accepted.

For the moderating effects (H11a–H11i), mixed results were observed. The moderating effects of Gender on the relationships between CK, PK, and TK with BI (H11a–H11c) were not statistically significant. Similarly, Age did not moderate the relationships between CK and BI (H11d) or PK and BI (H11e), and Teaching Experience did not moderate the relationships between CK and BI (H11g) or PK and BI (H11h). These hypotheses were therefore rejected.

In contrast, Age was found to significantly moderate the relationship between Technological Knowledge and Behavioural Intention (H11f), and Teaching Experience also significantly moderated the relationship between Technological Knowledge and Behavioural Intention (H11i). These findings indicate that the effect of Technological Knowledge on Behavioural Intention varies across age groups and levels of teaching experience. Consequently, H11f and H11i were accepted.

Overall, the structural model demonstrates strong support for the proposed direct relationships, while moderation effects were evident only for Technological Knowledge, highlighting its differential influence across demographic and experiential groups.

Table 4.14
Summary of the findings from the structural model assessment

No.	Hypothesis	Results	Decision
H1	PE → BI	Significant	Accepted
H2	EE → BI	Significant	Accepted
H3	SI → BI	Significant	Accepted
H4	FC → BI	Significant	Accepted
H5	HM → BI	Significant	Accepted
H6	HT →BI	Significant	Accepted
H7	PK →BI	Significant	Accepted
H8	CK → BI	Significant	Accepted
H9	TK →BI	Significant	Accepted
H10	BI →AU	Significant	Accepted
H11a	Gender × CK	Not Significant	Rejected
H11b	Gender × PK	Not Significant	Rejected
H11c	Gender × TK	Not Significant	Rejected
H11d	Age × CK	Not Significant	Rejected
H11e	Age × PK	Not Significant	Rejected
H11f	Age × TK	Significant	Accepted
H11g	Teaching Experience × CK	Not Significant	Rejected
H11h	Teaching Experience × PK	Not Significant	Rejected
H11i	Teaching Experience × TK	Significant	Accepted

4.5 Conclusion

The structural model assessment demonstrates strong support for the proposed relationships in the study. All core constructs, including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Habit, and the TPACK knowledge components, were found to significantly predict Behavioural Intention, which in turn significantly predicted Actual Use. These findings confirm the robustness of the integrated model in explaining behavioural intention and technology use among academic staff.

The analysis of moderating effects revealed that Gender and Age did not significantly moderate the relationships between Content Knowledge or Pedagogical Knowledge and Behavioural Intention, indicating a largely consistent influence of these knowledge components across demographic groups. However, Age and Teaching Experience were found to significantly moderate the relationship between Technological Knowledge and Behavioural Intention, suggesting that the effect of technological knowledge varies across different age groups and levels of professional experience.

Overall, the structural model results indicate that while the direct pathways of the model are stable and well supported, moderation effects are selective and construct-specific, occurring only in relation to Technological Knowledge. These findings provide a clear empirical foundation for the subsequent discussion of theoretical and practical implications in the next chapter.

CHAPTER FIVE
DISCUSSION AND RECOMMENDATIONS

5.0 Introduction

This chapter discusses and interprets the empirical findings presented in Chapter 4 by situating them within the theoretical and empirical literature reviewed in Chapter 2. The discussion is explicitly structured according to the research objectives and research questions, with a focus on explaining how technology acceptance, knowledge readiness, and individual differences shape the adoption of Blended Learning (BL) among academic staff at UTHM.

Drawing on the integrated UTAUT2–TPACK framework, this chapter examines the significance of the direct relationships between technology acceptance constructs and academic staff's Behavioural Intention to adopt BL, as well as the influence of core TPACK knowledge components (pedagogical knowledge, content knowledge, and technological knowledge) that were conceptualised in this study as indicators of knowledge readiness. These discussions highlight that BL adoption is influenced not only by favourable acceptance perceptions but also by academic staff's confidence in their underlying knowledge capabilities.

In addition, this chapter addresses the relationship between Behavioural Intention and Actual Use of BL, clarifying the extent to which intention translates into enacted practice within the institutional context of UTHM, including the use of the Learning Management System (LMS) and Full Online Classroom (FOC). The discussion further examines the selective moderating effects of demographic and experiential variables, with particular attention given to teaching experience, to explain variations in how

Technological Knowledge (TK) influences Behavioural Intention across different academic staff profiles.

Throughout the chapter, the findings are critically compared with prior studies on BL adoption and technology acceptance in higher education to identify areas of convergence and divergence, thereby strengthening the theoretical positioning and explanatory robustness of the study. The chapter also outlines the theoretical, methodological, and practical contributions of the research, acknowledges its limitations, and proposes directions for future research. It concludes with a synthesis of the key discussion points, providing a coherent foundation for the thesis's overall conclusions.

5.1 Overview of Research Objectives and Hypotheses

To provide a structured basis for discussing the empirical findings, this section revisits the research objectives, research questions, and hypotheses introduced in Chapter 1. These elements form the analytical framework through which the results presented in Chapter 4 are interpreted and critically discussed in this chapter.

Table 5.1 presents the alignment between the study's research objectives, corresponding research questions, and hypotheses. This alignment ensures conceptual clarity and provides a systematic reference point for examining the relationships between technology acceptance factors, knowledge readiness factors, Behavioural Intention, and Actual Use of BL, as well as the moderating effects of selected demographic and experiential variables among academic staff at UTHM.

Table 5.1
Summary of Research Objectives, Research Questions, and Hypotheses of the Study

No.	Research Objectives	Research Questions	Research Hypothesis
1.	To examine the influence of UTAUT2 variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit) on academic staff's Behavioural Intention to adopt and use BL as a teaching method in UTHM.	To what extent do UTAUT2 variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit) influence academic staff's Behavioural Intention to accept and use BL as a teaching method in UTHM?	**H1:** Performance Expectancy (PE) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H2:** Effort Expectancy (EE) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H3:** Social Influence (SI) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H4:** Facilitating Conditions (FC) have a significant influence on academic staff's Behavioural Intention to adopt BL. **H5:** Hedonic Motivation (HM) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H6:** Habit (HT) has a significant influence on academic staff's Behavioural Intention to adopt BL.
2.	To examine the influence of TPACK variables (pedagogical knowledge, content knowledge, and technological knowledge) on academic staff's Behavioural Intention to accept and use BL as a teaching method in UTHM.	To what extent do knowledge variables (pedagogical knowledge, content knowledge, and technological knowledge) influence academic staff's Behavioural Intention to accept and use BL as a teaching method in UTHM?	**H7:** Pedagogical Knowledge (PK) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H8:** Content Knowledge (CK) has a significant influence on academic staff's Behavioural Intention to adopt BL. **H9:** Technological Knowledge (TK) has a significant influence on academic staff's Behavioural Intention to adopt BL.
3.	To investigate the moderating effects of gender, age, and teaching experience on the relationship between TPACK knowledge components (pedagogical knowledge, technological knowledge, and content knowledge) and academic staff's Behavioural Intention to accept and use BL as a teaching method in UTHM	Do the demographic variables (gender, age, and teaching experience) moderate the relationship between the TPACK model factors (pedagogical, technological, and content knowledge) and academic staff's Behavioural Intention to accept and use BL as a teaching method in UTHM?	**H11a:** Gender moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI). **H11b:** Gender moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI). **H11c:** Gender moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI). **H11d:** Age moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI). **H11e:** Age moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI). **H11f:** Age moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).

			H11g: Teaching Experience moderates the relationship between Content Knowledge (CK) and Behavioural Intention (BI). **H11h:** Teaching Experience moderates the relationship between Pedagogical Knowledge (PK) and Behavioural Intention (BI). **H11i:** Teaching Experience moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI).
4.	To examine the influence of academic staff's Behavioural Intention on their actual use of BL as a teaching method in UTHM.	Does academic staff's Behavioural Intention to accept BL influence their Actual Use of BL as a teaching method in UTHM?	**H10:** Behavioural Intention (BI) has a significant influence on the Actual Use of BL (USE).

The first set of research objectives and hypotheses focuses on technology acceptance factors conceptualised under the UTAUT2 framework (Venkatesh et al., 2012). These hypotheses examine the effects of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit on academic staff's Behavioural Intention to adopt BL. Collectively, these constructs explain the motivational, social, and institutional drivers that shape academic staff's acceptance of BL as a teaching method.

The second set of objectives and hypotheses addresses knowledge readiness factors adapted from the core components of the TPACK framework (Mishra & Koehler, 2006), namely Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). In this study, these constructs are explicitly conceptualised as indicators of academic staff's perceived readiness and capability to engage with BL, rather than as direct measures of pedagogical implementation or instructional practice. This distinction enables the examination of how underlying knowledge confidence supports or constrains adoption intention.

The third research objective investigates the moderating roles of gender, age, and teaching experience in the relationships between knowledge readiness factors (TK, PK, and CK) and Behavioural Intention. This objective assesses whether the influence of knowledge readiness on adoption intention varies across demographic and experiential groups, thereby providing a more nuanced understanding of differential BL adoption patterns among academic staff.

The fourth research objective examines the relationship between Behavioural Intention and Actual Use of BL, consistent with the technology acceptance literature, which positions intention as a proximal determinant of enacted behaviour. These objectives address whether favourable acceptance and knowledge readiness translate into observable use of BL systems, including the Learning Management System (LMS) and Full Online Classroom (FOC), within the institutional context of UTHM.

Guided by the structure presented in Table 5.1, the discussion in this chapter is organised into two main parts. The first part examines the direct effects of UTAUT2 acceptance variables and TPACK-derived knowledge readiness factors on Behavioural Intention and Actual Use of BL. The second part explores the moderating effects of demographic and experiential variables, with particular attention to teaching experience, to explain variations in how technological knowledge influences Behavioural Intention across different academic staff profiles.

5.2 Discussion of Research Question 1

Influence of UTAUT2 Variables on Behavioural Intention

5.2.0 Performance Expectancy → Behavioural Intention

The findings of this study confirm that Performance Expectancy has a significant influence on Behavioural Intention to adopt BL among academic staff at UTHM. This finding aligns with recent post-pandemic studies demonstrating that educators are more inclined to adopt BL when it delivers clear and tangible performance benefits, rather than functioning as a supplementary or experimental teaching approach (Dwivedi et al., 2019; Al-Maroof et al., 2021; Salloum et al., 2023). Contemporary evidence suggests that academic staff are increasingly evaluating BL in terms of its contribution to workload management, teaching efficiency, and instructional continuity, reflecting a broader shift toward outcome-driven adoption decisions in higher education.

This performance-oriented evaluation is particularly salient within the Malaysian higher education context, where national digitalisation initiatives position BL as a strategic mechanism for enhancing institutional efficiency and learning flexibility. Policy frameworks, such as the Malaysia Education Blueprint and DePAN 2.0, explicitly frame BL as a response to increasing instructional demands, expanding student cohorts, and resource constraints. The strong influence of PE observed in this study suggests that academic staff acceptance of BL at UTHM is closely aligned with these policy imperatives, especially when BL supports structured course delivery through institutional platforms such as the Learning Management System (LMS) and Full Online Classroom (FOC), while simultaneously reducing administrative burden.

From a theoretical perspective, this finding reinforces the continued applicability of UTAUT2 in explaining technology acceptance within public higher education settings. Consistent with the discussion in Chapter 2, PE emerges as a robust and stable predictor of Behavioural Intention, even in post-adoption and post-pandemic contexts where digital teaching has become increasingly normalised. Practically, the results underscore the importance of institutional strategies that foreground the performance value of BL, including the systematic communication of evidence-based benefits, the dissemination of effective BL practices, and professional development initiatives aligned with measurable teaching and learning outcomes.

Overall, rather than functioning as a peripheral influence, Performance Expectancy emerges as a central mechanism through which academic staff evaluate the relevance and utility of BL in their professional practice. In a higher education environment characterised by heightened accountability, efficiency demands, and performance measurement, BL adoption is strongly shaped by its perceived instrumental value. This positions Performance Expectancy as a key leverage point linking individual acceptance decisions with broader institutional and policy-driven objectives in the implementation of BL at UTHM.

5.2.1 Effort Expectancy → Behavioural Intention

Effort Expectancy (EE), commonly conceptualised as perceived ease of use, reflects the extent to which individuals believe that a system can be used with minimal cognitive and operational effort. Early technology acceptance models, particularly the Technology Acceptance Model (TAM), positioned ease of use as a key antecedent of Behavioural Intention (Davis, 1989). This construct was subsequently retained in the UTAUT and UTAUT2 frameworks as a core predictor of intention, reflecting its role in reducing cognitive and operational barriers to technology use (Venkatesh et al., 2003; Venkatesh et al., 2012).

The findings of the present study indicate that Effort Expectancy significantly influences Behavioural Intention to adopt BL among academic staff at UTHM. This result is consistent with recent higher education studies, particularly in post-pandemic contexts, where rapid and sustained engagement with online and blended systems has heightened educators' sensitivity to system usability, workflow disruption, and cognitive load (Al-Maroof et al., 2021; Al-Fraihat et al., 2022; Alhumaid et al., 2023). Empirical evidence suggests that even academically experienced and digitally literate educators may resist the adoption of BL when supporting platforms are perceived as complex, unstable, or time-intensive to operate.

Recent literature further indicates that the role of Effort Expectancy has shifted from facilitating initial adoption to supporting sustained use. Rather than focusing on basic technological familiarity, academic staff increasingly evaluate BL systems based on how seamlessly they integrate with existing teaching workflows, assessment practices, and administrative responsibilities (Salloum et al., 2023). The significant effect of EE observed in this study, therefore, reflects a pragmatic orientation among academic staff, where perceived effort is closely linked to workload management, time efficiency, and system reliability.

Within the Malaysian higher education context, the influence of Effort Expectancy is particularly salient. As discussed in Chapter 2, academic staff in public universities often balance multiple teaching, research, and service commitments, amplifying the impact of perceived effort on adoption decisions. The present findings suggest that institutional efforts to promote BL adoption should prioritise user-centred Learning Management System (LMS) design, consistent technical support, and applied professional development focused on operational efficiency and authentic teaching scenarios. Reducing perceived system complexity is therefore central to sustaining academic staff engagement with BL.

Overall, this finding reinforces the continued relevance of Effort Expectancy within the UTAUT2 framework while extending its explanatory value to contemporary BL environments characterised by prolonged digital engagement. Rather than functioning solely as an entry-level adoption facilitator, Effort Expectancy emerges as a key indicator of system suitability within everyday academic practice, shaping Behavioural Intention through its influence on cognitive load, workflow integration, and perceived efficiency. In this way, usability and operational ease become critical factors in maintaining the adoption of BL in public university settings.

5.2.2 Social Influence → Behavioural Intention

Social Influence (SI), as conceptualised within the UTAUT framework, refers to the extent to which individuals perceive that important others, such as colleagues, supervisors, and institutional leaders, expect, encourage, or legitimise their use of a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). In BL contexts, SI reflects the normative processes through which institutional culture, leadership signals, and peer practices shape academic staff's Behavioural Intention to adopt BL-supported systems.

The findings of this study show that Social Influence significantly predicts Behavioural Intention to adopt BL among academic staff at UTHM. This result is consistent with recent evidence from higher education research, particularly in post-pandemic settings, where peer endorsement, leadership advocacy, and institutional expectations have been shown to play a decisive role in shaping educators' technology adoption decisions (Teo et al., 2021; Al-Maroof et al., 2021; Raman & Thannimalai, 2023). Instead of mainly acting as external pressure, contemporary literature increasingly presents SI as a form of professional validation, where educators are more likely to adopt BL when they see it as legitimate, valued, and widely practised in their academic communities.

The significance of Social Influence is especially pronounced within the Malaysian higher education context. As discussed in Chapter 2, public universities in Malaysia operate within relatively hierarchical and collectivist organisational cultures, where institutional direction and collegial consensus exert substantial influence on individual behaviour. Empirical studies from Asian higher education settings indicate that leadership endorsement, faculty-level advocacy, and visible peer adoption are particularly effective in reducing uncertainty and legitimising technology-related change (Yusoff et al., 2022; Kaur & Sidhu, 2023). The present findings therefore suggest that academic staff at UTHM are more likely to adopt BL when supported by departmental leadership and normalised via peer practices.

From a theoretical standpoint, this finding supports the continued relevance of UTAUT2 while highlighting the contextual sensitivity of social mechanisms in higher education. In this study, Social Influence operates less as a compliance-driven determinant and more as a facilitator of shared professional norms surrounding BL use, consistent with the conceptual discussion in Chapter 2. Practically, the results suggest the value of institutional strategies that leverage social mechanisms, such as leadership modelling, peer mentoring, and communities of practice, to embed BL within everyday academic culture.

Overall, rather than acting as an isolated determinant, Social Influence functions as a legitimising layer that reinforces individual acceptance decisions by signalling professional alignment and institutional support. In higher education environments characterised by collectivist norms and hierarchical structures, these social cues play a critical role in reducing uncertainty and sustaining engagement with BL, underscoring the importance of collective, culture-based approaches to technology adoption.

5.2.3 Facilitating Conditions → Behavioural Intention

Facilitating Conditions (FC) refer to academic staff's perceptions of the availability of organisational, technical, and infrastructural support required to use a system effectively. Within the UTAUT2 framework, FC capture the extent to which institutional readiness, access to resources, and ongoing technical support enable technology acceptance and intention formation (Venkatesh et al., 2012). In BL contexts, FC are particularly salient, as adoption depends not only on individual acceptance but also on the reliability of institutional systems such as the Learning Management System (LMS) and Full Online Classroom (FOC), as well as the availability of responsive support mechanisms.

The findings of this study indicate that Facilitating Conditions exert the strongest influence on Behavioural Intention to adopt BL among academic staff at UTHM. This result aligns with recent higher education studies, particularly in post-pandemic contexts, which highlight institutional support as a decisive factor in educators' intention to engage with blended and digital teaching approaches (Al-Fraihat et al., 2022; Al-Maroof et al., 2021; Rasheed et al., 2023). As BL becomes embedded as a routine mode of delivery, academic staff increasingly evaluate adoption based on the dependability of institutional systems, access to timely technical assistance, and clarity of organisational processes rather than individual experimentation.

Recent literature further demonstrates that Facilitating Conditions play a critical role in enabling the translation of favourable perceptions into stronger adoption intentions. Even when BL is perceived as useful and manageable, inadequate infrastructure, unstable platforms, or insufficient technical support can constrain adoption and undermine intention to adopt (Bond et al., 2021; Ghazal et al., 2023). The prominence of FC in this study, therefore, suggests that institutional readiness functions not merely as a background condition, but as an active enabler of BL adoption in public university settings.

This finding is particularly relevant within the Malaysian higher education context. As discussed in Chapter 2, national initiatives such as the Malaysia Education Blueprint (2015–2025) and the National e-Learning Policy (DePAN 2.0) explicitly prioritise infrastructure development, system integration, and academic staff support as key enablers of BL. The present results provide empirical support for these policy directions by demonstrating that academic staff's intention to adopt BL is closely tied to their confidence in the institution's capacity to deliver consistent organisational and technical support.

Overall, rather than serving as a secondary or supportive factor, Facilitating Conditions emerge as a structural anchor shaping BL adoption at UTHM. Academic staff appear more willing to commit to BL when institutional systems are perceived as reliable, support mechanisms are accessible, and organisational processes are stable. This highlights that acceptance is contingent not only on favourable perceptions of usefulness or ease of use, but also on confidence in institutional readiness, positioning Facilitating Conditions as a critical lever for strengthening Behavioural Intention to adopt BL in public higher education contexts.

5.2.4 Hedonic Motivation → Behavioural Intention

Hedonic Motivation (HM) refers to the degree of enjoyment or pleasure derived from using a technology, representing an intrinsic motivational determinant within the UTAUT2 framework (Venkatesh et al., 2012). Unlike performance- or effort-related beliefs, HM captures users' affective responses to technology use, reflecting whether interaction with a system is perceived as pleasant, satisfying, and engaging. In BL contexts, HM has become increasingly relevant as academic staff engage with platforms such as the Learning Management System (LMS) and Full Online Classroom (FOC) on a sustained basis rather than as short-term or emergency solutions.

The findings of this study indicate that Hedonic Motivation has a significant positive effect on Behavioural Intention to adopt BL among academic staff at UTHM. This supports the theoretical assumptions of UTAUT2, which posit that positive affective experiences enhance users' willingness to adopt and continue using technologies, particularly in organisational contexts where use is encouraged but not entirely mandatory (Venkatesh et al., 2012). In the BL context, HM reflects academic staff's enjoyment and satisfaction in interacting with BL-related systems rather than engagement with pedagogical design or instructional outcomes.

Recent post-pandemic studies in higher education further reinforce the relevance of HM in technology acceptance decisions. Empirical evidence suggests that enjoyment and positive user experience significantly influence educators’ continued engagement with digital and blended systems, especially following prolonged exposure to online platforms during and after the COVID-19 pandemic (Al-Maroof et al., 2021; Rasheed et al., 2023). As BL use has become routinised, academic staff increasingly evaluate technologies not only in terms of functionality and efficiency, but also based on emotional comfort, cognitive ease, and overall user experience.

Consistent with the discussion in Chapter 2, positive affective responses to technology use have been shown to reduce resistance and support confidence and sustained engagement with digital systems (Bond et al., 2021). When BL platforms are perceived as intuitive and satisfying rather than frustrating or burdensome, academic staff are more likely to maintain favourable attitudes toward continued use. In this respect, HM complements EE and HT by reinforcing engagement through positive system interaction rather than through external pressure or obligation.

From an institutional perspective, the significance of Hedonic Motivation highlights the importance of experiential system quality in BL adoption strategies. Beyond ensuring technical functionality, attention to interface design, system responsiveness, and user autonomy can enhance enjoyment and reduce negative affect associated with system use. Designing BL environments that are not only usable but also pleasant to engage with may therefore strengthen intrinsic motivation and support sustained adoption.

Overall, viewed through an affective acceptance lens, Hedonic Motivation emerges as a meaningful contributor to Behavioural Intention by shaping academic staff's emotional engagement with BL systems. Rather than trivialising adoption as enjoyment-driven, the findings indicate that positive affective experiences help lower resistance, reinforce habitual use, and stabilise long-term engagement. This underscores the continued relevance of affective motivation within UTAUT2 and highlights its role in sustaining BL adoption in post-pandemic higher education environments.

5.2.5 Habit → Behavioural Intention

Habit (HT) refers to the extent to which repeated prior experience with a technology leads to automatic or routinised patterns of use over time. Within the UTAUT2 framework, habit represents a post-adoption acceptance mechanism, whereby technology use shifts from conscious evaluation to automatic behaviour as familiarity increases (Venkatesh et al., 2012). From a behavioural perspective, habit reduces cognitive effort and uncertainty, making continued technology use less dependent on deliberate decision-making.

Prior research in information systems consistently demonstrates that habitual behaviour becomes a dominant driver of sustained technology use once initial adoption barriers have been overcome. Limayem and Cheung (2008) found that habit can exert a stronger influence on continued system use than Behavioural Intention in mature usage contexts, while LaRose et al. (2003) showed that repeated and positively reinforced interactions promote behavioural automaticity and reduce reliance on cognitive evaluations. These findings suggest that long-term technology engagement is often maintained through routine rather than active reassessment.

The findings of the present study indicate that Habit significantly influences Behavioural Intention to adopt BL among academic staff at UTHM. This supports the theoretical assumptions of UTAUT2, which posit that habitual use reinforces intention by increasing confidence, reducing perceived effort, and normalising technology use within everyday work routines (Venkatesh et al., 2012). In the BL context, academic staff who have developed routine familiarity with BL-related systems are therefore more likely to express stronger intentions to continue using them.

Recent post-pandemic higher education research further contextualises this finding. Extended periods of compulsory online and BL during the COVID-19 pandemic accelerated habit formation among educators, resulting in routinised engagement with digital platforms (Bond et al., 2021; Rasheed et al., 2023). As BL systems became embedded within standard academic processes, reliance on habitual behaviour increased, reducing the need for repeated evaluation of system usefulness or usability.

Institutional conditions also play a critical role in reinforcing habit formation by ensuring consistent exposure and stable system environments. Within UTHM, sustained implementation of the Learning Management System (LMS) and initiatives such as the Full Online Classroom (FOC) have likely contributed to repeated system use, facilitating the transition from intentional adoption to routine engagement. This institutionalisation strengthens the consolidation of BL practices beyond the initial acceptance phase.

Overall, rather than operating as a standalone predictor, Habit functions as a stabilising mechanism that consolidates BL adoption once systems become embedded within routine academic practice. By reducing cognitive effort and uncertainty, habitual engagement reinforces Behavioural Intention and supports sustained engagement. This highlights that long-term BL adoption is maintained not only through favourable perceptions of usefulness, ease of use, or institutional support, but also through repeated exposure and routine system interaction, underscoring the importance of habit formation in sustaining BL adoption in public higher education contexts.

5.3 Discussion of Research Question 2

Influence of Knowledge Readiness (TPACK Core Components) on Behavioural Intention

Academic staff's background knowledge constitutes a critical determinant of technology adoption, as effective engagement with BL-supported systems requires sufficient knowledge readiness rather than pedagogical enactment. In this study, the TPACK framework is employed specifically as a knowledge-based framework to operationalise academic staff's perceived knowledge across three core domains: Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK). Consistent with the framing in Chapter 2, these constructs are treated as independent yet complementary knowledge factors, rather than as indicators of instructional practice or pedagogical quality (Mishra & Koehler, 2006).

Prior research has established that educators' self-perceived knowledge across PK, CK, and TK is strongly associated with their confidence in engaging with technology-supported environments. Empirical studies demonstrate that when academic staff report higher levels of knowledge readiness, they are more likely to express positive behavioural intentions toward adopting blended and online systems (Scherer et al., 2019; Valtonen et al., 2022). Conversely, deficiencies in any one knowledge domain may constrain adoption intentions, even when institutional support and system availability are present. These findings align with the discussion in Chapter 2, which highlighted knowledge readiness as a necessary condition for technology acceptance beyond infrastructure provision.

5.3.0 Pedagogical Knowledge → Behavioural Intention

Pedagogical Knowledge (PK) in this study reflects academic staff's perceived understanding of teaching and learning principles rather than the enactment of pedagogical strategies. Its significant influence on Behavioural Intention indicates that educators who feel confident in their pedagogical understanding are more willing to engage with BL environments at a conceptual level. This suggests that confidence in pedagogical reasoning supports acceptance by reducing uncertainty about how BL aligns with teaching and learning processes.

This finding is consistent with recent evidence indicating that perceived pedagogical knowledge contributes to educators' readiness to engage with digital systems, even when pedagogical implementation is not directly examined (Valtonen et al., 2022). When academic staff perceive themselves as pedagogically competent, they are less likely to view BL as disruptive to instructional coherence, thereby strengthening their intention to adopt BL-supported systems.

5.3.1 Content Knowledge → Behavioural Intention

The significant influence of Content Knowledge (CK) on Behavioural Intention suggests that confidence in subject-matter expertise plays an important role in BL adoption. Academic staff who perceive themselves as possessing strong disciplinary knowledge are more inclined to engage with BL environments without concerns related to content dilution, disciplinary rigour, or academic credibility.

This finding supports prior research demonstrating that educators' confidence in their disciplinary foundations enhances their willingness to integrate technology into teaching contexts (Scherer et al., 2019; Valtonen et al., 2022). In the BL context, strong CK appears to function as a stabilising knowledge resource that enables academic staff to focus on system use rather than on safeguarding content integrity, thereby strengthening behavioural intention.

5.3.2 Technological Knowledge → Behavioural Intention

Technological Knowledge (TK) also emerged as a significant predictor of Behavioural Intention to adopt BL among academic staff at UTHM. This suggests that academic staff who perceive themselves as technologically knowledgeable are more likely to express positive intentions toward the adoption of BL. However, the influence of TK was found to be non-uniform, as it was moderated by age and teaching experience.

This finding aligns with post-pandemic studies, which show that technological knowledge does not exert a consistent effect across educator groups (Bond et al., 2021; Scherer & Teo, 2019). Higher levels of technological awareness may increase sensitivity to system limitations, workload implications, and institutional constraints, particularly among more experienced academic staff. This reinforces the importance of conceptualising TK not merely as a technical skill set, but as a contextualised knowledge factor that interacts with experience to shape acceptance decisions.

As discussed in Chapter 2, Malaysian higher education institutions, including UTHM, have invested substantially in digital platforms such as the Learning Management System (LMS) and Full Online Classroom (FOC). However, uneven utilisation and variable confidence among academic staff suggest that technological provision alone does not guarantee adoption. The present findings empirically support this position by demonstrating that perceived technological knowledge remains a decisive factor influencing Behavioural Intention, independent of infrastructural availability.

Overall, the findings for Research Question 2 confirm that knowledge readiness constitutes a critical explanatory layer in understanding the adoption of BL at UTHM. While technology acceptance constructs explain why academic staff intend to adopt BL, the TPACK-derived knowledge components explain whether they feel sufficiently equipped to do so. Pedagogical, content, and technological knowledge function as complementary readiness conditions that support acceptance by reducing uncertainty and strengthening confidence. Integrating TPACK core components with UTAUT2, therefore, provides a more comprehensive and context-sensitive explanation of BL adoption, highlighting the importance of strengthening academic staff's knowledge readiness to support sustained engagement with BL systems.

5.4 Discussion of Research Question 4

Influence of Behavioural Intention on Actual Use

5.4.0 Behavioural Intention → Actual Use

The relationship between Behavioural Intention (BI) and Actual Use (AU) is a foundational assumption in information systems and technology acceptance research. Behavioural theories, such as the Theory of Planned Behaviour and the UTAUT framework, posit that intention represents the most immediate cognitive antecedent of actual behaviour, provided that individuals possess sufficient capability and enabling conditions are in place (Ajzen, 1991; Venkatesh et al., 2012). Within BL adoption contexts, BI reflects academic staff's readiness and willingness to engage with BL-supported systems, while AU represents the extent to which this intention is translated into observable system use.

Consistent with these theoretical assumptions, the findings of the present study indicate a significant positive relationship between Behavioural Intention and Actual Use, confirming that academic staff who report stronger intentions to adopt BL are more likely to engage in actual BL system use at UTHM. This finding aligns with prior empirical evidence in higher education, which consistently identifies Behavioural Intention as a necessary precursor to technology use across a range of digital learning environments (Venkatesh et al., 2012; Scherer et al., 2017).

However, despite the statistical significance of the BI–AU relationship, the relatively modest coefficient of determination (R^2) for Actual Use suggests that intention alone explains only a limited proportion of BL actual use behaviour. This finding reflects the well-documented intention–use gap in technology adoption research, whereby favourable intentions do not always translate into consistent or sustained system use. Recent post-pandemic studies in higher education have highlighted that structural and contextual constraints, such as workload intensity, system reliability, administrative demands, and the availability of technical support, can restrict the extent to which intention is enacted in practice (Bond et al., 2021; Rasheed et al., 2023).

As discussed in Chapter 2, this distinction underscores the importance of differentiating between acceptance and enactment. While Behavioural Intention captures individual-level motivation and readiness, Actual Use is also shaped by institutional and system-level conditions that extend beyond individual control. The present findings suggest that although academic staff at UTHM demonstrate strong acceptance of BL at the intention level, actual use remains contingent upon the stability of institutional platforms such as the Learning Management System (LMS) and Full Online Classroom (FOC), the availability of ongoing technical support, and alignment with institutional processes and workload structures.

From a technology acceptance perspective, the BI–AU relationship observed in this study reinforces the central role of intention while simultaneously highlighting its limitations as a sole predictor of use. The findings indicate that Behavioural Intention functions as a necessary but insufficient condition for BL adoption, requiring reinforcement through facilitating conditions and adequate knowledge readiness to support sustained engagement with BL systems.

Overall, the results confirm that Behavioural Intention is a critical driver of Actual Use of BL at UTHM, consistent with established acceptance models. However, the modest explanatory power for Actual Use demonstrates that translating intention into practice depends on a broader configuration of acceptance factors, knowledge readiness, and institutional support. Addressing this intention–use gap is therefore essential for ensuring that positive attitudes toward BL are converted into consistent and sustainable system use within public higher education contexts.

5.5 Discussion of Research Question 3

Moderating Effects of Teaching Experience, Age, and Gender on the Knowledge–Intention Relationship

This section discusses the moderating effects of gender, age, and teaching experience on the relationships between knowledge readiness factors, which are Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK), and Behavioural Intention (BI) to adopt blended learning (BL). Overall, the findings reveal a selective rather than uniform moderation pattern, indicating that demographic and experiential variables do not exert consistent influence across all knowledge–intention relationships.

5.5.0 Gender as a Moderator

The findings of the present study indicate that gender does not significantly moderate the relationships between Content Knowledge (CK), Pedagogical Knowledge (PK), Technological Knowledge (TK), and Behavioural Intention (BI) to adopt BL. This suggests that male and female academic staff at UTHM exhibit comparable levels of adoption intention when differences in knowledge readiness are considered. The absence of a significant gender-moderating effect reflects a departure from earlier technology adoption research that reported gender-based differences in acceptance behaviour (Venkatesh et al., 2003; Gefen & Straub, 1997).

Earlier studies attributed gender differences in technology adoption to variations in confidence, socialisation, and differential access to digital technologies (Ong & Lai, 2006). However, more recent empirical evidence indicates that such disparities have diminished substantially in professional contexts where digital system use is a normative requirement rather than an optional activity. Studies conducted in higher education environments with established digital infrastructures report minimal or non-significant gender effects on technology acceptance and actual use intentions (Scherer et al., 2017; Bond et al., 2021). These findings support the interpretation that gender-based differences become less salient when access to technology, institutional expectations, and system exposure are relatively uniform.

As discussed in Chapter 2, Malaysian higher education institutions have implemented national- and institutional-level initiatives aimed at standardising access to digital systems and strengthening academic staff capacity for BL adoption. At UTHM, initiatives such as the implementation of the Full Online Classroom (FOC) and institution-wide Learning Management System (LMS) support have contributed to creating a consistent technological environment for academic staff. Such conditions are likely to reduce structural and experiential disparities that previously contributed to gender-based variation in technology acceptance.

Cultural and organisational contexts further influence the relevance of gender as a moderating factor. While gender-related differences in technology use may persist in certain societal contexts, recent studies focusing on higher education environments increasingly report limited gender effects when professional roles, access to digital systems, and organisational expectations are standardised (Wang et al., 2021; Rasheed et al., 2023). This reinforces the view that, within universities, technology acceptance decisions are shaped more strongly by knowledge readiness and institutional conditions than by gender.

Overall, the absence of a significant gender-moderating effect suggests that BL adoption at UTHM is not meaningfully differentiated by gender once knowledge factors are considered. From an institutional perspective, this implies that gender-specific intervention strategies may be unnecessary. Instead, efforts should prioritise inclusive, knowledge-focused support mechanisms that strengthen CK, PK, and TK across the academic workforce, reinforcing acceptance-based adoption rather than demographic segmentation.

5.5.1 Age as a Moderator

The findings indicate that age significantly moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI) to adopt BL. This suggests that the extent to which technological knowledge translates into adoption intention varies across age groups. Specifically, academic staff with higher levels of technological knowledge demonstrate stronger behavioural intentions to adopt BL, with this relationship being more pronounced among younger academic staff.

Earlier literature frequently explained age-related differences in technology adoption through the distinction between so-called "digital natives" and "digital immigrants" (Prensky, 2001). While this categorisation provided an initial lens for understanding generational differences, more recent studies caution against treating age as a deterministic factor. Contemporary research increasingly attributes variation in technology acceptance to differences in exposure, confidence, and familiarity with evolving digital systems rather than chronological age alone (Scherer et al., 2019; Bond et al., 2021). Nevertheless, age remains relevant insofar as it shapes opportunities for sustained engagement with digital technologies and patterns of technology-related experience.

The significant moderating effect of age on the TK–BI relationship observed in this study indicates that technological knowledge does not exert a uniform influence on adoption intention across age groups. Younger academic staff, who are more likely to have developed technological knowledge through continuous exposure during their education and early career stages, may perceive such knowledge as a facilitator of BL adoption. In contrast, older academic staff, even when possessing adequate levels of technological knowledge, may evaluate technology adoption more cautiously due to heightened sensitivity to system complexity, perceived effort, or the time investment required to maintain proficiency in rapidly evolving digital environments (Czaja & Lee, 2006; Vaportzis et al., 2017).

Importantly, age did not significantly moderate the relationships between Content Knowledge (CK) or Pedagogical Knowledge (PK) and Behavioural Intention. This finding suggests that these knowledge domains exert a relatively stable influence on BL adoption intention across age groups. As discussed in Chapter 2, CK and PK are typically accumulated through extended professional experience and formal academic training, resulting in comparable levels of confidence across career stages (Shulman, 1986; Valtonen et al., 2022). Consequently, age-related differences in BL adoption appear to be concentrated primarily within the technological knowledge domain rather than across all forms of professional knowledge.

Recent higher education studies support this pattern by demonstrating that age-related variation in technology adoption is most evident when adoption requires sustained interaction with rapidly changing digital systems (Scherer et al., 2019; Tondeur et al., 2023). In such contexts, technological knowledge functions as a dynamic capability that is more sensitive to continuous exposure and ongoing practice than to professional seniority alone.

Overall, the moderating role of age highlights that Technological Knowledge is the most age-sensitive knowledge domain influencing Behavioural Intention to adopt BL. While Content Knowledge and Pedagogical Knowledge consistently influence intention across age groups, technological knowledge exerts differential effects depending on age-related exposure and confidence. These findings suggest that institutional efforts to strengthen BL adoption should prioritise experience-sensitive approaches to developing technological knowledge, reinforcing acceptance through confidence-building and sustained support rather than assuming age-based resistance.

5.5.2 Teaching Experience as a Moderator

The findings indicate that teaching experience significantly moderates the relationship between Technological Knowledge (TK) and Behavioural Intention (BI) to adopt BL. This suggests that the extent to which technological knowledge influences adoption intention varies across career stages. In contrast, teaching experience does not moderate the relationships between Content Knowledge (CK) or Pedagogical Knowledge (PK) and BI, indicating that experiential differences are concentrated primarily within the technological knowledge domain.

The significant moderating effect of teaching experience on the TK–BI relationship highlights that technological competence is interpreted and evaluated differently depending on professional experience. Academic staff with fewer years of teaching experience are more likely to perceive technological knowledge as an enabling resource that supports BL adoption, particularly as digital systems have been embedded throughout their academic training and early professional exposure. For these staff members, higher levels of technological knowledge are more directly associated with confidence and a willingness to engage with BL platforms.

In contrast, academic staff with longer teaching experience may approach technological knowledge more cautiously. Even when adequate TK is present, adoption intention may be shaped by accumulated professional routines, prior experiences with institutional systems, and heightened sensitivity to perceived risks such as increased workload, system instability, or the need for continuous updating of digital skills. Recent technology acceptance research suggests that experienced professionals tend to evaluate new technologies pragmatically, placing greater emphasis on reliability, efficiency, and institutional alignment rather than on technological capability alone (Granić & Marangunić, 2019; Bond et al., 2021). As a result, Technological Knowledge does not translate into Behavioural Intention uniformly across experience levels.

This pattern is consistent with the UTAUT2 framework, which acknowledges that individual capabilities interact with post-adoption conditions, such as habit and facilitating conditions, to shape Behavioural Intention (Venkatesh et al., 2012). From this perspective, technological knowledge functions as a necessary but not sufficient condition for adoption among more experienced academic staff. Without supportive institutional conditions and contextual reinforcement, TK may be perceived as an additional cognitive or operational burden rather than as an enabler of BL adoption.

Importantly, the absence of moderation effects for Content Knowledge and Pedagogical Knowledge suggests that these knowledge domains are relatively stable across career stages. As discussed in Chapter 2, CK and PK are primarily developed through formal academic training, disciplinary engagement, and cumulative teaching practice, resulting in relatively consistent levels of confidence regardless of years of service (Schmidt et al., 2009; Valtonen et al., 2022). Consequently, variations in BL adoption intention associated with teaching experience are more strongly linked to differences in technological familiarity and confidence than to differences in disciplinary or pedagogical knowledge.

Recent empirical studies support this interpretation by demonstrating that professional experience enhances judgment and instructional decision-making but does not necessarily predict technological adaptability (Scherer et al., 2019; Rasheed et al., 2023). In such cases, experienced academic staff may possess strong content and pedagogical foundations, yet remain selective in adopting BL unless technological systems are perceived as stable, well-supported, and aligned with existing institutional practices.

Overall, the moderating role of teaching experience underscores that Technological Knowledge is the most experience-sensitive determinant of BL adoption intention. While Content Knowledge and Pedagogical Knowledge consistently influence behavioural intention across career stages, Technological Knowledge interacts with teaching experience to shape adoption decisions in more complex ways. These findings suggest that strengthening BL adoption requires not only enhancing technological knowledge but also addressing how such knowledge is experienced and evaluated across different career stages. Focusing on confidence, continuity, and institutional alignment is therefore crucial for ensuring inclusive and sustainable adoption of BL among academic staff.

5.6 Theoretical Contribution

5.6.0 Addressing Critical Research Gaps

Much of the existing literature on educational technology adoption has treated technology acceptance and educators' professional knowledge as conceptually related but analytically separate domains. Studies grounded in technology acceptance models, such as UTAUT2, have primarily focused on perceptual, motivational, and behavioural determinants of adoption, including perceived usefulness, effort expectancy, social influence, and habit. In contrast, research drawing on the TPACK framework has concentrated on educators' underlying knowledge domains (technological, pedagogical, and content knowledge) without explicitly linking these competencies to behavioural intention or technology use behaviour. This conceptual separation has resulted in a fragmented understanding of BL adoption, particularly within higher education contexts.

This study addresses this gap by empirically demonstrating that Behavioural Intention (BI) to adopt BL is shaped not only by acceptance-related perceptions but also by academic staff's levels of knowledge readiness. The findings show that Technological Knowledge, Pedagogical Knowledge, and Content Knowledge function as cognitive foundations that support or constrain adoption intention. In this respect, favourable acceptance perceptions alone are insufficient to explain BL adoption if academic staff lack adequate knowledge resources to engage confidently with BL-supported systems. The integration of TPACK therefore provides an essential explanatory layer that complements UTAUT2 by clarifying why positive attitudes toward BL do not always translate into intention or sustained engagement.

Importantly, this study reconceptualises TPACK within adoption research as a knowledge readiness framework rather than as a model of pedagogical execution or instructional quality. By operationalising PK, CK, and TK as individual knowledge factors influencing Behavioural Intention, the study avoids conflating instructional practice with adoption behaviour. This addresses a limitation in prior TPACK-based studies, which often infer pedagogical effectiveness without explicitly examining how educators' knowledge readiness shapes their willingness to adopt technology.

In addition, the study addresses a further gap in the literature by identifying the selective moderating role of teaching experience in the relationship between Technological Knowledge and Behavioural Intention. While many UTAUT2 and TPACK studies implicitly assume that technological competence exerts a uniform effect across users, the present findings demonstrate that the translation of technological knowledge into adoption intention is contingent upon experience-related factors. By revealing that teaching experience conditions the influence of TK, while PK and CK remain stable across career stages, the study provides a more nuanced explanation of BL adoption among academic staff.

Overall, this study bridges acceptance-based and knowledge-based perspectives within a single explanatory framework. In doing so, it challenges the assumption that favourable technology perceptions are sufficient for adoption and advances a more integrated understanding of BL adoption that accounts for both motivational and cognitive readiness dimensions.

5.6.1 Implications for Theory

From a theoretical perspective, the findings of this study extend existing technology adoption models by demonstrating that acceptance and knowledge readiness are interdependent processes rather than parallel or independent constructs. While UTAUT2 effectively explains why academic staff may be inclined to adopt BL through behavioural, motivational, and social mechanisms, the inclusion of TPACK-derived knowledge factors explains whether educators perceive themselves as cognitively prepared to do so. This integration advances adoption theory by positioning knowledge readiness as a necessary complement to acceptance mechanisms.

The study further refines the theoretical role of TPACK by clarifying its function within adoption research. Rather than conceptualising TPACK as a model of pedagogical enactment or instructional competence, this study frames Pedagogical Knowledge, Content Knowledge, and Technological Knowledge as individual cognitive resources that influence Behavioural Intention. This theoretical repositioning avoids conflation between instructional practice and adoption behaviour and enables a more precise explanation of how educators perceived knowledge confidence shapes technology acceptance decisions. In doing so, TPACK is reconceptualised as a readiness-oriented framework that operates upstream of pedagogical implementation.

In addition, the findings extend UTAUT2 by demonstrating that its explanatory power is strengthened when acceptance constructs are examined alongside knowledge readiness factors. Acceptance mechanisms such as facilitating conditions, habit, and hedonic motivation are shown to operate more meaningfully when users possess sufficient technological knowledge to engage with digital systems. These results indicate that acceptance constructs do not function in isolation but are contingent upon users' cognitive preparedness and confidence in navigating blended learning environments.

The study also contributes to theory by highlighting the selective role of individual difference variables in shaping adoption processes. The moderating effects of age and teaching experience on the relationship between Technological Knowledge and Behavioural Intention demonstrate that knowledge-related influences are not uniformly distributed across user groups. This finding challenges assumptions in both UTAUT2- and TPACK-based studies that technological knowledge exerts a consistent effect on adoption intention and underscores the importance of examining conditional relationships within integrated adoption models.

Finally, by empirically validating an integrated UTAUT2–TPACK (knowledge-based) model in a Malaysian public university context, this study contributes to theory by offering a contextually grounded yet theoretically generalisable framework for understanding BL adoption among academic staff. The findings demonstrate that adoption is shaped by the interaction between acceptance-related perceptions and knowledge readiness, advancing current understanding of technology adoption beyond surface-level acceptance models. This theoretical integration provides a robust foundation for future research examining technology adoption in higher education contexts where both motivation and cognitive readiness must be jointly considered.

5.7 Methodological Contribution

This study makes a methodological contribution to blended learning research by presenting a rigorous, transparent, and contextually appropriate analytical approach for examining complex acceptance- and knowledge-based relationships in higher education. Through the integration of robust sampling procedures, systematic data screening, and advanced multivariate analysis, the study strengthens the methodological foundations of educational technology adoption research, thereby enhancing the reliability, validity, and reproducibility of its findings.

A key methodological contribution lies in the application of Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS to analyse the interrelationships among multiple latent constructs. This approach is particularly appropriate for BL adoption research, where technology acceptance factors, knowledge readiness components, and behavioural outcomes operate simultaneously rather than independently. Unlike traditional regression-based techniques, PLS-SEM enables the estimation of complex structural models that incorporate direct, indirect, and moderating effects within a single analytical framework, thereby capturing the multidimensional and nonlinear nature of technology adoption in authentic educational settings.

The study further advances methodological rigour through a systematic data screening and validation process conducted prior to model estimation. Multivariate outlier detection using Mahalanobis distance was employed to identify and remove extreme cases that could distort parameter estimates, ensuring that the final dataset accurately represented the target population. In addition, assessments of normality and multicollinearity were conducted to confirm the robustness of the dataset for multivariate analysis. These procedures enhance the credibility of the statistical findings and address methodological weaknesses commonly observed in survey-based research on educational technology.

Another methodological contribution is the explicit examination of potential response bias and common method variance. By achieving a high response rate and conducting Harman's single-factor test, the study reduced the likelihood that the observed relationships were artefacts of the measurement method rather than substantive theoretical effects. This strengthens confidence in the internal validity of the findings and addresses a frequent critique of cross-sectional survey research in higher education contexts.

The study also extends methodological practice by incorporating predictive relevance (Q^2) and effect size (f^2) analyses alongside conventional significance testing. The assessment of predictive relevance demonstrates that the integrated model exhibits stronger explanatory power for Behavioural Intention than for Actual Use, offering a more nuanced understanding of where acceptance-based models are most effective and where additional explanatory mechanisms may be required. Effect size analysis further clarifies the relative importance of predictors, enabling differentiation between statistically significant relationships and those with substantive explanatory value.

Additionally, the inclusion of moderation analysis using the product indicator approach represents a significant methodological advancement. By examining how age and teaching experience condition the effects of Technological Knowledge on Behavioural Intention, the study moves beyond average effects to reveal subgroup-specific adoption dynamics. This approach demonstrates the value of modelling interaction effects in educational technology research and provides a more refined methodological lens for understanding heterogeneity within academic populations.

Collectively, these methodological choices establish a transparent and replicable framework for investigating technology adoption in higher education. The study provides a robust methodological template for future research examining complex, context-dependent phenomena that involve behavioural, technological, and knowledge-based constructs. By prioritising rigorous data validation, multivariate modelling, predictive assessment, and moderation analysis, this research contributes to elevating methodological standards in blended learning and educational technology scholarship.

5.8 Practical contribution

The integration of BL within Malaysian higher education represents a strategic response to growing demands for instructional flexibility, continuity, and digital readiness. Given the diversity of institutional contexts and uneven levels of technological preparedness across public universities, the findings of this study provide practical, evidence-based guidance for institutional leaders, policymakers, and academic development units seeking to strengthen BL adoption among academic staff.

First, the identification of key UTAUT2 determinants offers clear direction for institutional strategy. The findings demonstrate that academic staff are more inclined to adopt BL when they (i) perceive clear performance-related benefits, (ii) experience minimal operational complexity, and (iii) observe visible endorsement from peers and institutional leadership. Practically, this suggests that universities should move beyond generic BL promotion and instead explicitly communicate how BL enhances teaching efficiency, assessment management, student engagement, and learning continuity. Demonstrating tangible instructional gains, rather than emphasising policy compliance, aligns BL adoption with academic staff's performance-oriented motivations.

From an institutional and policy perspective, BL initiatives should therefore prioritise value-driven implementation rather than mandate-driven adoption. Institutional policies that link BL use to improved teaching outcomes, workload optimisation, and flexible course delivery are more likely to gain academic buy-in. This approach also supports national higher education digitalisation agendas by positioning BL as a pedagogical enabler rather than an administrative requirement.

The strong influence of Facilitating Conditions (FC) highlights the critical role of institutional readiness in sustaining BL adoption. Reliable learning management systems, stable internet connectivity, responsive technical support, and clear implementation guidelines emerged as essential enablers. The findings suggest that even when academic staff hold positive attitudes toward BL, adoption is unlikely to be sustained without confidence in institutional support structures. Universities should therefore prioritise system reliability, reduce administrative friction, and ensure that technical assistance is timely and accessible, particularly during peak teaching periods.

Social Influence (SI) also emerged as a significant determinant of BL adoption, underscoring the importance of collective norms and leadership endorsement within Malaysian higher education institutions. Visible commitment from senior management, faculty-level champions, and peer role models plays a decisive role in legitimising BL practices. Practically, this supports the establishment of communities of practice, peer mentoring schemes, and recognition mechanisms that normalise BL use and reduce uncertainty associated with adoption. Such initiatives are particularly effective in collectivist institutional cultures where professional norms strongly influence individual behaviour.

Importantly, the findings related to knowledge readiness, grounded in the TPACK framework, provide actionable insights for academic development planning. The significant effects of Pedagogical Knowledge, Content Knowledge, and Technological Knowledge suggest that BL adoption is closely linked to academic staff's perceived readiness to integrate technology pedagogically, rather than simply exposure to digital tools. Professional development initiatives should therefore adopt a TPACK-informed approach, focusing on how technology can be meaningfully aligned with subject content and instructional strategies, rather than offering tool-based or platform-centric training in isolation. This distinction ensures that adoption readiness is supported without conflating it with teaching performance evaluation.

The moderating effects of age and teaching experience further reinforce the need for differentiated support strategies. The findings indicate that technological knowledge does not translate uniformly into adoption intention across experience levels. Consequently, a one-size-fits-all training approach is unlikely to be effective. Institutions should design tiered support mechanisms that recognise variation in technological confidence, prior exposure, and instructional routines. For example, early-career academic staff may benefit from advanced pedagogical innovation workshops, while more experienced staff may require scaffolded support that integrates BL gradually into established teaching practices. Such differentiation enhances the efficiency of institutional investment and promotes the adoption of more inclusive BL across diverse academic profiles.

Overall, the practical contribution of this study lies in its ability to translate empirical findings into targeted, context-sensitive guidance for the implementation of BL. By aligning institutional strategies with empirically validated acceptance- and knowledge-based determinants, Malaysian higher education institutions can create enabling environments in which BL adoption is sustainable, equitable, and embedded within everyday academic practice, rather than remaining an episodic or compliance-driven initiative.

5.9 Limitations of the Study

Despite the contributions of this study, several limitations should be acknowledged, as they may influence the interpretation and generalisability of the findings.

First, the study relied exclusively on self-reported survey data, which may be subject to common method bias and social desirability effects. Academic staff may have overestimated their behavioural intentions or knowledge-related capabilities when responding to the questionnaire. Although validated measurement instruments were employed and rigorous data screening procedures were undertaken, self-reported measures cannot fully capture actual teaching behaviour. Future research could enhance construct validity by incorporating complementary qualitative methods, such as interviews or reflective accounts, to gain a deeper insight into how academic staff perceive and experience the adoption of BL.

Second, the study was conducted within a single public higher education institution, Universiti Tun Hussein Onn Malaysia (UTHM). While this institutional focus enabled a detailed and contextually grounded analysis, it may limit the generalisability of the findings to other Malaysian universities or international higher education settings. Variations in institutional leadership, technological infrastructure, academic culture, and professional development practices may result in different adoption patterns. Future studies employing multi-institutional or cross-university designs would allow for comparative analysis and enhance the external validity of BL adoption models.

Third, although the study acknowledged the influence of national digitalisation initiatives such as the Malaysia Education Blueprint and DePAN 2.0, macro-level policy and environmental factors were not explicitly modelled. Variables such as funding structures, institutional governance mechanisms, and broader socio-economic conditions were beyond the scope of this research. Consequently, the findings primarily reflect individual-level acceptance and knowledge readiness within a specific institutional context. Future research could integrate organisational- or policy-level variables to provide a more comprehensive, multi-level understanding of BL adoption in higher education.

Another limitation relates to the study's emphasis on behavioural intention rather than long-term patterns of actual use. While behavioural intention is a well-established predictor of technology adoption, it does not necessarily guarantee sustained or consistent implementation over time. The cross-sectional design of this study limits the ability to examine changes in adoption behaviour, habit formation, or shifts in usage patterns. Longitudinal research designs could offer valuable insights into how

BL adoption evolves and stabilises across academic semesters or institutional transitions.

Finally, the exclusive use of a quantitative research approach may have constrained the exploration of contextual and experiential factors such as workload pressures, discipline-specific constraints, and institutional change processes. Although these factors may indirectly influence technology acceptance and knowledge readiness, they were not explicitly examined in this study. Incorporating qualitative perspectives from academic staff and institutional stakeholders in future research could enrich understanding of these contextual dynamics and support more nuanced interpretations of BL adoption.

Overall, addressing these limitations in future research would enhance the robustness of BL adoption studies and contribute to a more comprehensive, context-sensitive understanding of technology acceptance and knowledge readiness in higher education.

5.10 Future Research

Building on the findings of this study and the ongoing evolution of BL implementation in Malaysian higher education, several directions for future research are proposed. These recommendations aim to extend theoretical understanding of BL adoption while strengthening empirical inquiry into technology acceptance and knowledge readiness.

First, future studies should adopt longitudinal research designs to examine the sustainability and evolution of BL adoption over time. While the present study provides robust evidence of the relationships among acceptance factors, knowledge factors, Behavioural Intention, and Actual Use, longitudinal approaches would enable researchers to observe how these relationships change as BL becomes increasingly routinised. Such designs would be particularly valuable for examining habit formation, the development of technological knowledge, and the stability of adoption intention across academic semesters or institutional transitions.

Second, future research should extend the integrated UTAUT2–TPACK model across multiple institutions and institutional types. Comparative studies involving different public universities, private institutions, or technical and vocational education settings would help determine whether the relative influence of acceptance- and knowledge-based factors varies across organisational contexts. This would enhance the generalisability of the proposed model and support cross-institutional benchmarking of BL adoption readiness.

Third, there is scope for more explicit examination of contextual and cultural influences on technology acceptance and knowledge readiness. In collectivist and hierarchical environments, such as Malaysia, factors like leadership expectations, institutional norms, and professional culture may interact with individual acceptance perceptions and knowledge confidence. Future studies could incorporate organisational culture or leadership-related constructs to refine the understanding of how acceptance mechanisms operate within specific socio-cultural and institutional settings.

Fourth, future research should investigate factors that constrain or mediate the translation of Behavioural Intention into Actual Use. Although this study confirms a significant BI–AU relationship, the modest explanatory power for actual use suggests the presence of unmeasured structural or contextual constraints. Future models could explicitly incorporate variables such as workload demands, time availability, system reliability, and policy alignment to better explain the intention–use gap identified in this study.

Fifth, further research could explore knowledge development trajectories, particularly with respect to Technological Knowledge. Given the significant moderating effects of age and teaching experience identified in this study, future investigations could examine how technological knowledge develops across career stages and how changes in knowledge readiness influence acceptance over time. Longitudinal or quasi-experimental designs may provide valuable insight into how shifts in technological confidence relate to adoption intention.

Finally, future research may extend acceptance- and knowledge-based models to emerging technologies within BL environments, such as artificial intelligence–supported teaching tools and learning analytics systems. Rather than focusing solely on pedagogical design, such studies could examine how perceived usefulness, effort expectancy, and knowledge readiness influence academic staff's willingness to engage with next-generation educational technologies. This would further extend the relevance of UTAUT2 and knowledge-based frameworks in rapidly evolving digital learning ecosystems.

Collectively, these directions build on the present study by advancing a more nuanced, context-sensitive, and theoretically integrated understanding of BL adoption. Continued examination of the interaction between technology acceptance and knowledge readiness will support more robust, sustainable, and evidence-informed approaches to digital transformation in higher education.

5.11 Conclusion

This chapter has synthesised the findings presented in Chapter 4 through critical discussion and theoretical integration, highlighting the key contributions of the study to Blended Learning (BL) research within the context of Universiti Tun Hussein Onn Malaysia (UTHM). The discussion provides strong empirical support for the integrated UTAUT2–TPACK framework, confirming that both technology acceptance factors and knowledge readiness factors play a decisive role in shaping academic staff's Behavioural Intention and Actual Use of BL.

The findings reaffirm the significance of core UTAUT2 constructs, particularly Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, in influencing the adoption of BL. At the same time, the inclusion of TPACK knowledge domains extends existing acceptance models by demonstrating that academic staff's Content Knowledge, Pedagogical Knowledge, and Technological Knowledge strengthen Behavioural Intention and support the translation of intention into actual use. Rather than positioning knowledge as a pedagogical intervention, the findings indicate that knowledge readiness functions as an enabling condition that supports acceptance-based decision-making.

The moderation analysis further revealed that age and teaching experience selectively influence the relationship between Technological Knowledge and Behavioural Intention, highlighting that technological knowledge does not operate uniformly across academic staff profiles. This finding underscores the importance of recognising differential experience-based patterns in BL adoption rather than assuming homogeneous acceptance behaviour among academic staff.

Methodologically, the study contributes to educational technology research through the rigorous application of PLS-SEM, comprehensive measurement and structural model validation, and systematic moderation analysis. These methodological choices enhance the robustness and credibility of the findings, providing a replicable analytical framework for future research examining technology acceptance and BL adoption in higher education contexts.

From a practical perspective, the chapter offers evidence-based insights for institutional leaders and policymakers in Malaysia. The findings highlight the importance of strengthening facilitating conditions, reducing perceived effort associated with BL systems, and fostering supportive institutional environments that normalise and sustain BL use. Aligning technological infrastructure, system usability, and knowledge-focused support mechanisms is essential for ensuring that BL adoption is both feasible and sustainable among academic staff.

Finally, this chapter has outlined strategic directions for future research, emphasising the need for longitudinal investigations, cross-institutional comparisons, deeper examination of contextual and demographic influences, and further exploration of emerging technologies within BL environments from a technology acceptance perspective. Together, these directions reinforce the positioning of BL as a long-term institutional practice shaped by acceptance mechanisms and knowledge readiness rather than as a short-term technological response.

In conclusion, this study provides a comprehensive, empirically validated, and contextually grounded understanding of BL adoption among academic staff at UTHM. By integrating technology acceptance and knowledge-based determinants within a single explanatory framework, the study makes a meaningful contribution to theory, methodology, and practice, offering transferable insights for advancing BL implementation in Malaysian higher education and comparable institutional contexts.

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APPENDICES

Appendix A Table for Determining Sample Size for a Finite Population

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size. *S* is sample size.

Source: Krejcie & Morgan, 1970

The Table is constructed using the following formula for determining sample size:

Formula for determining sample size

$$s = X^2NP(1-P) \div d^2(N-1) + X^2P(1-P)$$

s = required sample size.

X^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841).

N = the population size.

P = the population proportion (assumed to be .50 since this would provide the maximum sample size).

d = the degree of accuracy expressed as a proportion (.05).

Source: Krejcie & Morgan, 1970

Appendix B Adopted/Adapted Constructs with Justification

This table outlines each construct used in the study, the originating model (UTAUT2 or TPACK), whether the items were adapted, and a brief justification:

Construct	Model	Adopted / Adapted	Justification
Performance Expectancy (PE)	UTAUT2	Adapted	Adjusted to reflect BL's role in enhancing teaching performance.
Effort Expectancy (EE)	UTAUT2	Adapted	Modified for ease of integrating BL in academic settings.
Social Influence (SI)	UTAUT2	Adapted	Adapted for peer and institutional influence in university contexts.
Facilitating Conditions (FC)	UTAUT2	Adapted	Focused on infrastructure and support specific to BL.
Hedonic Motivation (HM)	UTAUT2	Adapted	Reworded to reflect enjoyment in using BL tools.
Habit (HT)	UTAUT2	Adapted	Framed around tech use routines in teaching.
Behavioural Intention (BI)	UTAUT2	Adapted	Tailored to future BL usage intentions.
Actual Use (AU)	UTAUT2	Adapted	Measured via frequency-based use of BL in teaching.
Technological Knowledge (TK)	TPACK	Adapted	Adapted for knowledge of digital teaching tools.
Pedagogical Knowledge (PK)	TPACK	Adapted	Contextualised to Malaysian pedagogical practices.
Content Knowledge (CK)	TPACK	Adapted	Framed for subject mastery in BL environments.

Appendix C Questionnaire

COLLEGE OF ARTS AND SCIENCES

UNIVERSITI UTARA MALAYSIA

The Driving Factors Affecting the Adoption of Blended Learning Based on UTAUT2 and TPaCK

Dear Respondents,

Thank you for taking the time to participate in this survey, which investigates the factors influencing the adoption of blended learning in instructional practices. Specifically, this study examines the key factors that encourage teachers to adopt blended learning. This research is a significant requirement for the PhD in Instructional Technology program.

Please complete the questionnaire as accurately as possible. We assure you that all responses will remain confidential. No identifying information is requested, so your identity will remain anonymous.

The questionnaire should take approximately 20 minutes to complete. Your cooperation is highly appreciated.

If you have any questions or recommendations, please contact the researcher using the details provided below.

Thank you for your willingness to participate in this survey.

Principal investigator

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THANK YOU FOR YOUR COOPERATION!

Directions: While completing the questionnaire, please remember that we use blended learning by university academicians in teaching and learning. Blended learning is any learning where traditional (face-to-face) lecturing/teaching in a classroom is combined with computer-mediated instruction methods (e.g. online tests or tutorials, posting of lecture notes, videos or other course-related content on the Internet, etc.), which encompasses any technology specific to your teaching area.

PART A

You are required to choose the best answer that suits your choice by just ticking (√) or writing your answer in the space provided

1. Gender
   - ☐ Male
   - ☐ Female

2. Age Range
   - ☐ Under 35 years old
   - ☐ 36 – 50 years old
   - ☐ Above 50 years old

3. Working Experience
   - ☐ Below 5 years
   - ☐ 6 – 15 years
   - ☐ More than 15 years

4. Designation
   - ☐ Professor
   - ☐ Senior Lecturer
   - ☐ Associate Professor
   - ☐ Lecturer
   - ☐ Other, please specify (RA, Instructor, Tutor, Teacher, etc.)

     ____

5. Faculty
   - ☐ Centre of Co-curricular
   - ☐ Centre for Diploma Studies
   - ☐ Centre for Graduate Studies
   - ☐ Centre for Language Studies
   - ☐ Continuing Education Centre
   - ☐ Faculty of Engineering Technology
   - ☐ Faculty of Applied Science & Technology
   - ☐ Faculty of Technical & Vocational Education
   - ☐ Faculty of Electrical & Electronic Engineering
   - ☐ Faculty of Technology Management & Business
   - ☐ Faculty of Civil Engineering & Built Environment
   - ☐ Faculty of Mechanical & Manufacturing Engineering
   - ☐ Faculty of Computer Science & Information Technology

PART B

The following set of sections relates to your thoughts on Blended Learning. All questions in the survey will use a six-point Likert scale to measure responses. Please **CIRCLE** the number that denotes the answer to each question.

Strongly disagree 1	Disagree 2	Slightly disagree 3	Slightly agree 4	Agree 5	Strongly agree 6

a. Performance Expectancy

		Strongly Disagree	←→				Strongly Agree
PE1	Using Blended Learning would improve my teaching performance	1	2	3	4	5	6
PE2	Using Blended Learning helps me to accomplish teaching tasks more quickly	1	2	3	4	5	6
PE3	Using Blended Learning increases my productivity	1	2	3	4	5	6
PE4	Using Blended Learning would enhance my effectiveness in teaching	1	2	3	4	5	6

b. Effort Expectancy

		Strongly Disagree	←→				Strongly Agree
EE1	Learning how to use Blended Learning for my class is easy for me	1	2	3	4	5	6
EE2	It is easy for me to become skilful at implementing Blended Learning	1	2	3	4	5	6
EE3	I find Blended Learning easy to use in my class	1	2	3	4	5	6
EE4	My interaction with Blended Learning is clear and understandable	1	2	3	4	5	6

c. Social Influence

		Strongly Disagree	←→				Strongly Agree
SI1	People who are important to me think I should use Blended Learning	1	2	3	4	5	6
SI2	People who influence my behaviour think that I should use Blended Learning	1	2	3	4	5	6

SI3	People whose opinions I value prefer that I use Blended Learning	1	2	3	4	5	6
SI4	In general, the organisation has supported the use of Blended Learning	1	2	3	4	5	6

d. Facilitating conditions

		Strongly Disagree ⟷					Strongly Agree
FC1	I have the resources necessary to use Blended Learning in my class	1	2	3	4	5	6
FC2	Blended Learning is compatible with other technologies I use	1	2	3	4	5	6
FC3	I can get help from others when I have difficulties using Blended Learning	1	2	3	4	5	6

e. Hedonic Motivation

		Strongly Disagree ⟷					Strongly Agree
HM1	Using Blended Learning is fun	1	2	3	4	5	6
HM2	Using Blended Learning is enjoyable	1	2	3	4	5	6
HM3	Using Blended Learning is very entertaining	1	2	3	4	5	6

f. Habit

		Strongly Disagree ⟷					Strongly Agree
HT1	The use of Blended Learning has become a habit for me	1	2	3	4	5	6
HT2	I must use Blended Learning	1	2	3	4	5	6
HT3	Using Blended Learning has become natural to me	1	2	3	4	5	6

g. Technological Knowledge in conducting Blended Learning

		Strongly Disagree ⟷					Strongly Agree
TK1	I know how to solve ICT-related problems during Blended Learning sessions	1	2	3	4	5	6
TK2	I keep up with important new technologies that are useful for Blended Learning session	1	2	3	4	5	6

TK3	I know a lot of different technologies that I can use for Blended Learning	1	2	3	4	5	6
TK4	I have the technical skills I need to use technology for a successful Blended Learning session	1	2	3	4	5	6

h. Pedagogical Knowledge in conducting Blended Learning

		Strongly Disagree	←		→		Strongly Agree
PK1	I know how to assess student's performance	1	2	3	4	5	6
PK2	I can adapt my teaching based on what students currently understand or do not understand	1	2	3	4	5	6
PK3	I can adapt my teaching style to different learners	1	2	3	4	5	6
PK4	I can assess student learning in multiple ways	1	2	3	4	5	6
PK5	I can use a wide range of teaching approaches	1	2	3	4	5	6
PK6	I am familiar with a wide range of practices, strategies, and methods of teaching	1	2	3	4	5	6
PK7	I know how to motivate students to learn	1	2	3	4	5	6

i. Content Knowledge in conducting Blended Learning

		Strongly Disagree	←		→		Strongly Agree
CK1	I have sufficient knowledge in developing content in my discipline	1	2	3	4	5	6
CK2	I have various ways and strategies for developing my understanding of my discipline	1	2	3	4	5	6
CK3	I know the basic theories and concepts of my discipline	1	2	3	4	5	6
CK4	I know the history and development of important theories in my discipline	1	2	3	4	5	6
CK5	I am familiar with recent research in my discipline	1	2	3	4	5	6

j. Behavioral Intention to Use Blended Learning

		Strongly Disagree ↔ Strongly Agree					
BI1	I intend to continue using Blended Learning in the future	1	2	3	4	5	6
BI2	I will always try to use Blended Learning in my daily work	1	2	3	4	5	6
BI3	I plan to continue to use Blended Learning frequently	1	2	3	4	5	6

k. Actual Use of Blended Learning

AU1 Integration of Blended Learning Tools

"To what extent do you integrate various blended learning tools (e.g., learning management systems, online forums, multimedia resources) into your teaching practices?"

- ☐ 1 - Not at all
- ☐ 2 - Very slightly
- ☐ 3 - Slightly
- ☐ 4 - Moderately
- ☐ 5 - Very much
- ☐ 6 - Extremely

AU2 Student Engagement with Blended Learning Content

"How frequently do your students engage with blended learning content outside of the classroom (e.g., accessing online materials, completing online assignments, participating in online discussions)?"

- ☐ 1 - Never
- ☐ 2 - Very rarely
- ☐ 3 - Rarely
- ☐ 4 - Sometimes
- ☐ 5 - Often
- ☐ 6 - Always

AU3 Adaptation and Customization of Blended Learning Strategies

"How often do you adapt and customise blended learning strategies to meet the specific needs of your courses and students?"

- ☐ 1 - Never
- ☐ 2 - Very rarely
- ☐ 3 - Rarely
- ☐ 4 - Sometimes
- ☐ 5 - Often
- ☐ 6 - Always

THANK YOU FOR YOUR COOPERATION!

Appendix D Application Letter for Instrument Evaluation Panel

PUSAT PENGAJIAN PENDIDIKAN DAN BAHASA MODEN
SCHOOL OF EDUCATION AND MODERN LANGUAGES
College of Art and Sciences
Universiti Utara Malaysia
06010 UUM SINTOK
KEDAH DARUL AMAN
MALAYSIA

UUM
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Tel: 604-928 5381
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Laman Web (Web): www.seml.uum.edu.my

Prof. Madya Ts. Dr. Md Fauzi Bin Ahmad @ Mohamad
Ketua Jabatan
Jabatan Pengurusan Pengeluaran dan Operasi
Fakulti Pengurusan Teknologi dan Perniagaan
Universiti Tun Hussein Onn Malaysia
mohdfauzi@uthm.edu.my

20-9-2020

Tuan/Puan,

PELANTIKAN SEBAGAI PANEL PENILAI INSTRUMEN KAJIAN PERINGKAT DOKTOR FALSAFAH

Dengan segala hormatnya dimaklumkan bahawa pelajar berikut adalah calon Doktor Falsafah secara penyelidikan di Pusat Pengajian Pendidikan dan Bahasa Moden, Kolej Sastera dan Sains, Universiti Malaysia, Sintok, Kedah.

2. Butiran pelajar adalah seperti berikut:

Nama Penuh	**: AFFAH BINTI MOHD APANDI**
No. Matrik	**: 902827**
Peringkat Pengajian	**: Doktor Falsafah (Pendidikan)**
Tajuk Kajian	**: The Driving Factors Affecting the Adoption of Blended Learning in UTHM based on UTAUT2 and TPACK**

3. Sehubungan dengan itu, tuan/puan telah dikenal pasti dan dipilih untuk menjadi panel pakar kajian berdasarkan kepakaran dan pengalaman dalam bidang yang berkaitan. Untuk itu, disertakan borang jawapan dan mohon dikembalikan kepada affah_mohd_apandi@ahsgs.uum.edu.my untuk tindakan selanjutnya. Sebarang pertanyaan boleh berhubung terus dengan Puan Affah Binti Mohd Apandi di talian 012-9931598.

Kerjasama tuan/puan dalam menjayakan penyelidikan ini amatlah dihargai dan didahului dengan ucapan terima kasih.

"ILMU BUDI BAKTI"

Saya yang menjalankan tugas

(PM/ DR. ARUMUGAM A/L RAMAN)
Penyelia Pelajar
Pusat Pengajian Pendidikan dan Bahasa Moden
Universiti Utara Malaysia

Universiti Pengurusan Terkemuka
The Eminent Management University

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20-9-2020

Tuan/Puan,

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Saya yang menjalankan tugas

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Penyelia Pelajar
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Tuan/Puan,

PELANTIKAN SEBAGAI PANEL PENILAI INSTRUMEN KAJIAN PERINGKAT DOKTOR FALSAFAH

Dengan segala hormatnya dimaklumkan bahawa pelajar berikut adalah calon Doktor Falsafah secara penyelidikan di Pusat Pengajian Pendidikan dan Bahasa Moden, Kolej Sastera dan Sains, Universiti Malaysia, Sintok, Kedah.

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Kerjasama tuan/puan dalam menjayakan penyelidikan ini amatlah dihargai dan didahului dengan ucapan terima kasih.

"ILMU BUDI BAKTI"

Saya yang menjalankan tugas

(PM. DR. ARUMUGAM A/L RAMAN)
Penyelia Pelajar
Pusat Pengajian Pendidikan dan Bahasa Moden
Universiti Utara Malaysia

Appendix E Instrument Evaluation Panel Consent Form

UUM
Universiti Utara Malaysia

PERSETUJUAN MENJADI PANEL PAKAR UNTUK KESAHAN INSTRUMEN

Saya seperti nama di bawah bersetuju menjadi panel pakar dalam kajian pelajar bernama Affah Binti Mohd Apandi (No. Matrik : 902827) yang bertajuk :

THE DRIVING FACTORS AFFECTING THE ADOPTION OF BLENDED LEARNING IN UTHM BASED ON UTAUT2 AND TPACK

Nama : ______________________

No. Tel : ______________________

Email : ______________________

Universiti : ______________________

Jawatan : ______________________

Fakulti : ______________________

Bidang Kepakaran : ______________________

Penyerahan instrumen kajian:

1. Soal selidik diserahkan secara bersemuka. ☐
2. Soal selidik diserahkan secara email. ☐
3. Soal selidik diserahkan secara pos. ☐

______________________ ______________________

(Tandatangan) Cop

Appendix F Content Validity Form

PENGESAHAN PAKAR TERHADAP INSTRUMEN KAJIAN

Adalah dengan ini saya mengesahkan bahawa saya telah membuat semakan instrumen kajian sebenar pelajar berikut:

NAMA	: AFFAH BINTI MOHD APANDI
NO MATRIK	: 902827
PENGAJIAN	: DOKTOR FALSAFAH
BIDANG PENGAJIAN	: PENDIDIKAN
FAKULTI	: AWANG HAD SALLEH GRADUATE SCHOOL OF ARTS AND SCIENCES
TAJUK	: THE DRIVING FACTORS AFFECTING THE ADOPTION OF BLENDED LEARNING IN UTHM BASED ON UTAUT2 AND TPACK

ULASAN PAKAR:

____

____

____

____

____

Tandatangan : ______________________

Nama : ______________________

Jawatan : ______________________

Jabatan : ______________________

Cop Rasmi

ASSESSMENT ON THE DRIVING FACTORS AFFECTING THE ADOPTION OF BLENDED LEARNING IN UTHM BASED ON UTAUT2 AND TPACK

Direction: this tool asks for your evaluation of the questionnaire to be used in the data gathering for the investigation stated above, to establish its validity. You are required to give your honest assessment using the criteria stated below; please check (√) only one from the selection.

Scale: 5 – Excellent 4 – Very Good 3 – Good 2 – Fair 1 – Poor

	5	4	3	2	1
1. Clarity and Directions of Items The vocabulary level, language, structure and conceptual level of participants. The test directions and the items are written in a clear and understandable manner.					
2. Presentation and Organisation of Items The items are presented and organised in logical manner.					
The questionnaire is framed in a clear and simple order to avoid risk error.					
3. Suitability of Items The item appropriately presented the substance of the research. The questions are designed to determine the factors that are supposed to be measured.					
4. Adequateness of the Content The number of the questions per area is a representative enough of all the questions needed for the research.					
5. Attainment of Purpose The instrument as a whole fulfils the objectives needed for the research.					
6. Objective Each item question requires only one specific answer or measures only one behavior and no aspect of the questionnaires suggests in the past of the researcher.					
The questionnaire has the ability to distinguish the characteristics or the properties of differing attributes of the subjects under study.					
7. Scale and Evaluation Rating The scale adapted is appropriate for the item.					
8. Time Frame Quick and complete data can be generated by the questionnaire within the time frame allowed to obtain the data.					
The questionnaire has the capability to measure items of variables within a given time frame					

Ratings of overall questionnaire

Scale	Interpretation	Description
5	Very high valid	The questionnaire is very high valid and can provide unbiased data for the investigation, allowing 0-5% error
4	High valid	The questionnaire is high valid and can provide unbiased data for the investigation, allowing 8-10% error
3	Valid	The questionnaire is valid and can provide unbiased data for the investigation, allowing 11-15% error
2	Less valid	The questionnaire less valid and can provide unbiased data for the investigation, allowing 16-20% error
1	Not valid at all	The questionnaire is not valid and can provide unbiased data for the investigation, allowing 21-25% error

Indicators	Rating				
	5	4	3	2	1
The questionnaire is capable of generating data that will be of value and practical use to the sectors concerned in the investigation.					

Comments and suggestions:

Signature and official stamp