

Building the Future: Attitude, Knowledge, Digital Skills, and Adaptability in Student Learning

Wan Edura Wan Rashid*, Norfadzilah Abdul Razak², Shamsul Bahrin Saihani³

Institute of Business Excellence, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

*Corresponding Author

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ABSTRACT

This study examined the critical role of attitude, knowledge, digital skills, and adaptability in shaping student learning outcomes, focusing on their collective influence in preparing learners for future challenges. The research was conducted at a local university, surveying 250 students to explore the interrelationships among these key factors. A structured questionnaire was designed to capture data on students' attitudes towards learning, their knowledge base, proficiency in digital skills, and adaptability to dynamic educational environments. The survey aimed to evaluate how these elements interacted and contributed to enhanced learning experiences and academic success. The data collected were analyzed using a Structural Equation Modeling (SEM) approach via the Smart PLS software, enabling a comprehensive understanding of the causal relationships among variables. SEM was chosen for its robust capability in assessing complex models and validating hypothesized relationships. The findings revealed significant positive correlations between students' attitudes and their adaptability, as well as between digital skills and knowledge acquisition. These efforts will ensure students are well-prepared to navigate the demands of a rapidly evolving educational and professional landscape. This research contributes to the growing body of knowledge on integrating technological and pedagogical advancements in education, offering actionable insights for educators, policymakers, and curriculum designers.

Keywords: Attitude, Knowledge, Digital Skills, Student Learning Adaptability, Digital Learning

INTRODUCTION

Advanced technology has dramatically transformed the landscape of learning and education, reshaping how knowledge is acquired, shared, and applied. Schools, colleges, and universities are leveraging these advancements to prepare an ideal learning environment that equips students with the skills necessary for success in a rapidly evolving world [1]. From interactive digital platforms to AI-driven personalized learning tools, educational institutions are embracing innovation to enhance engagement, accessibility, and efficiency in teaching. These technologies allow for a more tailored approach to education, catering to individual learning styles and paces [2]. Virtual classrooms, augmented reality, and online collaboration tools are breaking down geographical barriers, enabling global connectivity and access to diverse resources. Moreover, institutions are integrating STEM (Science, Technology, Engineering, and Mathematics) and digital literacy into their curricula to prepare students for a tech-driven future [3]. By fostering creativity, critical thinking, and adaptability, educators are shaping learners who are not only academically competent but also equipped to thrive in complex, real-world environments. This shift in education underscores the need for a holistic approach that combines traditional knowledge with advanced digital skills and a growth mindset. As technology continues to advance, educational institutions remain at the forefront of preparing students to become lifelong learners and innovators, ready to tackle the challenges and opportunities of tomorrow [4].

A. Challenges in Students' Adaptability towards Technology

The integration of technology into education has introduced numerous benefits, but it has also presented significant challenges in terms of students' adaptability [5]. Many learners struggle to keep pace with the rapid evolution of digital tools, often facing issues such as a lack of technical proficiency or access to reliable devices and internet connectivity. For some, the transition from traditional learning methods to tech-driven platforms can be overwhelming, particularly for those unaccustomed to self-directed or virtual learning environments [6]. Additionally, disparities in digital skills among students create a divide, leaving some at a disadvantage in utilizing technology effectively. The overwhelming volume of information and the constant demand to multitask in digital spaces can also lead to cognitive overload, reducing learning efficiency [7]. To address these challenges, educational institutions must focus on providing equitable access, robust technical support, and targeted training to ensure that all students can adapt and thrive in a technology-enhanced educational environment.

B. Learning Adaptability

Learning adaptability in university settings has become an essential skill for students navigating the complexities of higher education. As universities integrate diverse teaching methodologies, technological advancements, and interdisciplinary curricula, students are required to adjust their learning strategies and approaches to succeed in these dynamic environments. Adaptability involves the ability to respond effectively to new challenges, assimilate different learning styles, and embrace innovative tools and resources [8].

University students often face diverse academic demands, including complex coursework, collaborative projects, and exposure to unfamiliar subjects. Adaptability enables them to manage these challenges by fostering resilience, problem-solving, and flexibility [9]. For instance, adapting to virtual or hybrid learning environments, which have become increasingly prevalent, demands a mastery of digital tools and self-directed learning skills. Additionally, students must adjust to the varying expectations of professors and the evolving requirements of their academic programs [10]. Beyond academic contexts, learning adaptability prepares students for real-world scenarios. Employers value graduates who can quickly learn and apply new skills, adapt to changing industry trends, and navigate diverse work environments. Thus, universities play a crucial role in cultivating this trait by incorporating experiential learning, cross-disciplinary courses, and technology-integrated education into their curricula [11]. Ultimately, learning adaptability is not just about coping with change but thriving in it. By embracing adaptability, university students can develop a lifelong learning mindset that equips them for personal and professional success in an ever-evolving global landscape. Institutions must prioritize fostering this skill to prepare students for the demands of the future.

C. Students Attitude and Learning Adaptability

The relationship between students' attitudes and adaptability has been a key focus of research in educational psychology, given its importance in fostering success in dynamic academic and social contexts. Attitude is often described as a psychological tendency to evaluate objects, events, or situations positively or negatively, which significantly influences behavior and decision-making [12]. Adaptability, on the other hand, refers to the capacity to adjust effectively to changes, challenges, and novel demands [13]. The interaction between these two constructs has revealed important insights into student development and learning outcomes. Research has consistently shown that a positive attitude enhances students' adaptability. Positive attitudes, characterized by optimism, openness to change, and resilience, enable students to approach challenges with confidence and a problem-solving mindset [14]. Martin et al. (2013) had highlighted that students with a positive outlook are more likely to embrace new experiences, persist through difficulties, and demonstrate greater academic and social flexibility. Furthermore, a positive attitude fosters motivation, which acts as a catalyst for adaptive behaviors in diverse learning environments [15]. Therefore, the following hypothesis was developed.

Hypothesis 1: Student's attitude has a significant relationship with students' adaptability to learn.

D. Digital Skills and Learning Adaptability

The integration of technology in education has emphasized the importance of digital skills in shaping students' ability to adapt to diverse and rapidly evolving learning environments. Digital skills, defined as the ability to use digital devices, communication applications, and networks effectively, are increasingly recognized as essential for fostering learning adaptability [16]. Learning adaptability refers to the capacity to adjust to new educational demands, methodologies, and contexts. The relationship between digital skills and adaptability has been the subject of extensive research, highlighting their interconnectedness and implications for modern education. Empirical studies agree that digital skills are significant to navigate diverse learning platforms and online resources, and digital collaboration tools, which enhance their ability to transition between traditional and online learning environments [17]. Meanwhile a study by [18] has asserted that digital skills allow students to locate, evaluate, and synthesize information from various sources, enabling them to adapt to complex learning tasks. Moreover, digital skills encourage self-directed learning by providing access to online courses, tutorials, and virtual communities, fostering adaptability to future educational or professional requirements [19]. Therefore, the next hypothesis was:

Hypothesis 2: Digital skill has a significant relationship with students adaptability to learn.

E. Knowledge and Learning Adaptability

Knowledge and learning adaptability are closely connected concepts in educational research. Knowledge, defined as the understanding and awareness of information, concepts, and processes, serves as a foundation for students' ability to adjust to new learning contexts [20]. Learning adaptability, which refers to the capacity to respond effectively to changes in academic demands, environments, or technologies, is increasingly valued in dynamic and ever-evolving educational systems. Knowledge plays a critical role in fostering adaptability by equipping students with the tools necessary to navigate new and challenging learning environments [21]. A broad and deep knowledge base is particularly significant for learning adaptability, as it enables cognitive flexibility, allowing students to apply learned concepts to novel situations [22]. This flexibility is crucial for problem-solving and critical thinking, both of which are essential components of adaptability [22]. Additionally, students with a strong knowledge base can transfer skills and concepts from one context to another, facilitating smoother transitions between learning environments or disciplines. Moreover, a study by a study had emphasized that students with a strong knowledge base can transfer skills and concepts from one context to another, facilitating smoother transitions between learning environments or disciplines[23]. Finally, with knowledge, student's confidence and self-efficacy created as that students who believe in their knowledge and skills are more likely to embrace challenges and adopt adaptive strategies [24]. Therefore, the third hypothesis was:

Hypothesis 3: Knowledge has a significant relationship with students adaptability to learn.

METHODOLOGY

A quantitative research was conducted on a population of university students from local universities. The convenience sampling technique was used on full-time and part time local students, who has experience using a learning management system. There were 175 of students participating in this study. Shown in Table 1, is a summary of the demographic profile of the participants.

TABLE I DEMOGRAPHIC FACTORS

Demographic Factors	n	Frequency (%)
Gender		
Female	85	48.57
Male	90	51.43

Mode of Study		
Full-Time	115	65.71
Part -Time	60	34.28
Semester		
3	55	31.43
4	25	14.28
5	67	38.28
6	28	16.00

The items used in the questionnaire were adapted from previous studies and used a five point Likert scale: 1= strongly disagree to 5= strongly agree. The data was analyzed based on the Structural Equation Model (SEM) using Smart PLS..

Composite reliability (CR) is a key indicator of internal consistency and assesses the extent to which the items within a construct produce similar results. The acceptable threshold for composite reliability is a value greater than 0.7 [25] Values above this benchmark indicate that the items are reliable and consistently reflect the underlying construct. Similarly, average variance extracted (AVE) is another measure of convergent validity, with a recommended value of 0.5 or higher to demonstrate that the construct explains a sufficient proportion of the variance in its indicators [26]. By ensuring that CR values exceeded 0.7 and validating other criteria such as AVE, the measurement model establishes the robustness of the constructs and their ability to represent the theoretical framework accurately. This process is critical in structural equation modeling (SEM) to ensure the validity and reliability of the proposed relationships among variables.

Once the measurement model was validated for reliability and validity, the structural model was analyzed to test the hypothesized relationships between the constructs. In the structural model, path coefficients represent the strength and direction of the relationships between constructs. These are evaluated based on their significance and magnitude. Significance testing is typically conducted using bootstrapping and providing t-values and p-values to assess the statistical significance of the paths [27]. Moreover, the R square (R²) value measures the variance explained by the independent constructs for the dependent construct. Values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively [28]. This indicates how well the predictors explain the endogenous variables. Moreover, The f² effect size evaluates the impact of each exogenous construct on an endogenous construct. The values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively [29]. Finally, in the structural model, the blindfolding procedure assesses the model's predictive relevance.

FINDINGS

A. Measurement Model

Table 2 shows the result of factors loading and convergent validity of the constructs. For attitude, there were five items and all items had a high factor loading with a outer loading value greater than 0.7 and above. Knowledge, digital skills and students' adaptability were found to have outer loadings which were greater than the threshold values and it was concluded that all the items highly represented the constructs. In addition, the composite reliability for attitude (CR = 0.50), knowledge (CR = 0.920), students' adaptability (CR= 0.854) and digital skills (0.950) indicated that all the constructs were highly internally consistand as suggested by [30] the composite reliability should be higher than 0.7 to indicate that the constructs are meaningful to the intent of a study. Next, the average variance extracted (AVE) values were greater than 0.5- the attitude (AVE = 0.793), knowledge (AVE = 0.697), students adaptability (0.541) and digital skills (AVE= 0.792). It was concluded that all variance explained greater than 50 percent of the constructs.

The result as shown in Table 3, revealed the discriminant validity in the structural equation model that was evaluated using the Heterotrait-Monotrait Ratio (HTMT) criterion. The values of HTMT should be greater

than 0.85 to 0.90 and if the values were greater than 0.9 then the result indicates discriminant issues in the model [31]. This method ensures that the constructs are distinct and not overly correlated by analyzing the ratio of between-construct correlations to within-construct correlations. The HTMT values will help confirm that each construct measures a unique concept within the model, with acceptable thresholds indicating satisfactory discriminant validity. The result showed that the values of the constructs were within the threshold values and confirmed that there were no discriminant issues in this model.

TABLE 2 CONVERGENT VALIDITY

Constructs	Indicator	Outer Loading	CR	AVE
Attitude	AL1	0.897	0.950	0.793
	AL2	0.913		
	AL3	0.888		
	AL4	0.871		
	AL5	0.883		
Knowledge	KL1	0.840	0.920	0.697
	KL2	0.844		
	KL3	0.847		
	KL4	0.847		
	KL5	0.797		
Students Adaptability	OLR1	0.774	0.854	0.541
	OLR2	0.711		
	OLR3	0.752		
	OLR4	0.650		
	OLR5	0.784		
Digital Skills	SL1	0.885	0.950	0.792
	SL2	0.911		
	SL3	0.930		
	SL4	0.849		
	SL5	0.874		

TABLE 3 CONVERGENT VALIDITY

Constructs	1	2	3	4
1. Attitude				
2. Knowledge	0.743			
3. Student's Adaptability	0.779	0.768		
4. Digital Skills	0.681	0.865	0.748	

B. Structural Model

Table 4 shows the result of path coefficient and hypotheses testing. The R square value was 0.543 and the R adjusted value was 0.539 indicating that 53.9 percent of students' adaptability was explained by attitude and digital skills. Additionally, the result as attitude ($\beta= 0.393$, t value= 5.947; $p < 0.005$), digital skills ($\beta= 0.239$, t value= 2.913; $p < 0.005$) and knowledge ($\beta= 0.191$, t value= 2.32; $p < 0.005$) indicated that all the hypotheses were supported as the t -values were greater than 1.962 and p values were less than 0.05. However, the effect size of attitude ($f^2= 0.172$), digital skills ($f^2= 0.026$), and knowledge ($f^2= 0.02$) were small effects towards students' adaptability. The results confirmed by the lower and upper limits that there

was no zero in between the values which indicated that all results were significant between the independent and dependent variables [31].

TABLE IV PATH COEFFICIENT

Hypothesis	β	STD	T-values	P values	F-Values	LL	UL
Attitude -> Student's _Adaptability	0.393	0.066	5.947	0.00	0.172	0.265	0.522
Digital skill -> Student's _Adaptability	0.239	0.082	2.913	0.004	0.226	0.088	0.411
Knowledge -> Student's _Adaptability	0.191	0.082	2.332	0.02	0.245	0.027	0.348

The final assessment was the cross-validated predictive ability test (CVPAT) representing an alternative to the PLS for a prediction-oriented assessment of the PLS-SEM results. As shown in Table 5 the results indicated that the PLS-SEM values were less than the LM values for all indicators showing a high predictive power [32].

TABLE 5 PREDICTIVE RELEVANCE

Indicators	Q ² predict	PLS SEM	LM
OLR1	0.286	1.216	1.217
OLR2	0.302	1.274	1.333
OLR3	0.284	1.419	1.482
OLR4	0.198	1.562	1.571
OLR5	0.336	1.353	1.371

The relationship between students' attitudes and their adaptability has been a significant focus of educational psychology, as both factors play a critical role in determining students' success in dynamic academic and social environments. Adaptability, often defined as the ability to adjust to new circumstances, challenges, and demands, is increasingly vital in contemporary education systems, where students face rapid technological advancements, diverse learning environments, and shifting expectations. Similar to [5], attitude is a pivotal factor influencing students' adaptability. A positive attitude fosters resilience, motivation, and engagement, enabling students to navigate the complexities of academic and social environments [12].

Furthermore, knowledge is a critical factor influencing students' adaptability, shaping their ability to navigate and respond to changing academic and social environments. Knowledge provides the essential tools and resources students need to make informed decisions and respond effectively to new situations [33]. For example, students with a strong understanding of digital tools are more likely to adapt quickly to online learning platforms, whereas those with limited knowledge may struggle to engage effectively. Similar to [34], knowledge is significant to fulfill the demands of the 21st century which continues to evolve, so equipping students with relevant and transferable knowledge is essential for their success.

The ability to adapt to rapidly evolving environments has become a crucial skill for students. Digital skills, which encompass the ability to use digital tools, technologies, and platforms effectively, play a pivotal role in shaping students' adaptability. As education increasingly integrates technology into teaching and learning, students with strong digital skills are better positioned to navigate and thrive in dynamic academic and social landscapes. This study explored how digital skills influenced students' adaptability, highlighting both opportunities and challenges. Hence, digital skills enable students to navigate and excel in dynamic academic and professional environments. Proficiency in digital tools fosters flexibility, problem-solving, and resilience, while a lack of digital skills poses significant challenges. By prioritizing digital skills, providing equitable access to technology, and creating supportive learning environments, educators can equip students with the digital competencies necessary to thrive in an increasingly interconnected and technology-driven world.

CONCLUSION

The combined influence of attitude, knowledge, and digital skills significantly shapes students' engagement in contemporary educational settings. A positive attitude fosters motivation, resilience, and openness to new challenges, which are crucial for active participation in learning. Knowledge serves as the foundation for confidence and informed decision-making, enabling students to engage deeply with academic content and contexts. Meanwhile, digital skills empower students to navigate modern learning environments effectively, facilitating collaboration, creativity, and access to diverse resources. Together, these factors create a holistic framework that drives meaningful engagement and ensures that students are prepared to succeed in an ever-evolving educational landscape.

The implication of this finding implies that educational institutions should implement strategies to cultivate growth mindsets and emotional resilience in students. Programs focusing on social-emotional learning (SEL) can enhance positive attitudes, leading to sustained students' engagement in learning platforms. More than that, universities should strongly emphasise interdisciplinary learning, problem-based approaches, and real-world applications which can deepen students' understanding and help them connect knowledge to their own experiences, increasing their engagement during teaching and learning. Finally, the university has to integrate digital skills into curricula is essential to prepare students for technology-driven learning environments. Workshops and hands-on training in digital tools can boost students' confidence and participation.

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