Personalized Education Path for Students; a Conceptual Basis for a Digitalized Education Environment

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Abstract
Learners come from different places and have other skills, abilities, and preferences when it comes to processing information, making sense of it, and using it in real life. Recently, Schools have continued to promote and pay for personalized learning on a large scale. Many learning institutions were closed for a long time, and the management opted for online learning. The main aim of this paper is to analyzes the personalized education path by discussing the right concepts and practices for students. To do this, the article focuses strictly on the digitalized education environment by examining the current trends and procedures leading to personalized education using the appropriate tools and techniques. The results have shown that students can integrate their learning using a digitally and technologically capable environment through a personalized education path. A personalized educational approach aids in preparing the future for the students through encouraging knowledge building.

Keywords—Personalized education path, Digital education, Education environment, Higher education, Virtual education.

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Introduction

Technology is becoming more common in classrooms, allowing students to connect in multimedia areas and extend their learning beyond traditional methods such as films and music (Baumöl & Bockshecker, 2017). As technology continues to improve and become more complex, it will affect traditional classrooms, with one of the most significant repercussions being its impact on classroom dynamics, especially between students and teachers. Technology is also having a growing effect on how students learn, and this trend will continue to affect how instructors and students interact and study. This chapter discusses the implications of new technology on students and teachers, with a focus on higher education, based on the results of learning science research. It highlights the need for research on student learning to identify emerging trends and leverage technology to enhance education.

There are signs that technology is facilitating learning both inside and outside the classroom. With a mobile device and internet connection, individuals can access a wealth of information. Networked devices have changed the way information is obtained, with people increasingly turning to online videos for practical instruction (Bejinaru, 2019). Multimedia resources and associated gadgets provide demonstrations of practically every operation, raising questions about how educators and educational institutions will adapt to a future with on-demand information and knowledge.

Since the printing press, new technologies have raised concerns in the classroom (Brudermann et al., 2019). Information and expertise are no longer the exclusive domain of conventional authoritative persons and institutions. With mobile devices, college students can access vast amounts of information online, interact with course materials and other students (Büth et al., 2018). However, concerns have been raised about how these devices affect children's learning and memory, and questions remain about how to incorporate technology into schooling without it becoming a distraction. Learning science investigates these trends and provides guidance to educators and students on how to utilize teaching tools to boost learning outcomes.

Background

Personalized education is a teaching approach that seeks to customize education for each student's unique needs, abilities, and interests. This approach differs from traditional education, which adopts a one-size-fits-all approach, where students are taught the same way and given the same material regardless of their individual differences. Personalized education aims to create a learning environment where
students can thrive based on their learning pace, interests, and cognitive abilities (Carreon, 2018).

The rise of technology has led to the digitalization of education, which has provided new opportunities for personalized education. Digital tools and technologies can be used to enhance personalized learning by providing tailored materials, assessments, and feedback for each student. This approach enables students to take more ownership of their learning and encourages them to be active learners rather than passive recipients of information (Wang & Chen, 2017).

The Personalized Education Path for Students is a conceptual framework that provides a basis for creating a digitalized education environment that is tailored to each student's needs. This framework is built on the idea that each student is unique and requires an individualized approach to learning. It emphasizes the use of digital tools and technologies to provide personalized learning experiences that enable students to reach their full potential (Lai & Wang, 2014).

Objective
While technology is being used more frequently in classrooms, its impact is perhaps most evident in higher education. A large portion of students' education is now online, mixed, flipped, or digital (Karakozov & Ryzhova, 2019), with students increasingly studying and researching online. Some commentators believe that these new approaches will change higher education forever, and this article discusses the principles and strategies for individualized education, utilizing appropriate tools and methodologies.

Literature Review
This section focuses on researchers' opinions and discussions about individualized education for students. Buckley-Marudas (2017) read internet discussion forums to learn about multicultural education, race, language, and socioeconomic position in the classroom. The paper provides a teaching strategy that contextualizes variation within significant learning areas. 10th-grade English students were given a secure venue to debate language, identity, and prejudices. Results revealed that students' democratic participation was enhanced. They learned to tolerate one another's quirks and avoid superficial preconceptions. In the online forum, students improved their critical literacy and expressed themselves openly and carefully (Mansilla et al., 2022).
Carreon (2018) has examined Facebook's potential as an online education tool. This study examined Facebook's influence on learning outcomes among Filipino seventh graders. A private Facebook group was created to distribute and debate multimedia files, text messages, and audio-visual presentations. According to the data, pupils who participated in the limited Facebook group improved their learning performance. Facebook increased learning results by allowing students to pick their learning pace, time, and place, similar to learning management systems with a built-in forum (Ramos et al., 2022). These strategies boost students' learning agency, improve their ability to work collaboratively, and motivate them to take chances. Digital technology may encourage student involvement, according to the study (Carreon, 2018). Digital communication and collaboration tools improve digital literacy, 21st-century skills, and learning results (Chang et al., 2018). Facebook and other externally run discussion platforms should be thoroughly evaluated before being used in education. Schools should employ LMSs with built-in discussion forums to secure students' personal information rather than Facebook (Puma et al., 2022). According to the literature review, this study raises the importance of analyzing the personalized education path by discussing the right concepts and practices for students.

Several studies have investigated the use of social media platforms for educational purposes. For example, a study by Manca and Ranieri (2016) explored the use of Twitter as a tool for collaborative learning among university students. The study found that Twitter facilitated communication and collaboration among students and allowed them to engage in discussions beyond the classroom. Similarly, a study by Kirschner and Karpinski (2010) examined the use of Facebook as an educational tool and found that it can enhance student engagement and communication.

Another study by Wang and Chen (2017) investigated the use of online discussion forums in a blended learning environment. The study found that students who participated in online discussions had higher levels of engagement and better learning outcomes compared to those who did not. The study also found that online discussion forums can facilitate peer-to-peer learning and promote critical thinking skills.

Additionally, a study by Lai and Wang (2014) explored the use of mobile devices for collaborative learning among college students. The study found that mobile devices can enhance student engagement and communication and improve learning outcomes. The study also found that the use of mobile devices can promote collaboration and active learning.

Overall, these studies suggest that digital communication and collaboration tools, including social media platforms and online
discussion forums, can enhance student engagement, promote collaboration, and improve learning outcomes. However, it is essential to evaluate the effectiveness and security of these tools before incorporating them into educational settings.

**Material and methodology**

*Data Collection and Processing*

The data for this study were collected by conducting a thorough review of articles related to personalized learning. To ensure the credibility of the data source, several evaluations emphasized the importance of using credible databases (Maseleno et al., 2018). Therefore, we selected Web of Science as the data source due to its reputation as a trustworthy archive of academic papers. The Social Sciences Citation Index within Web of Science contains "almost 3200 articles across 55 social science topics" and "selected material from 3500 of the world's greatest scientific and technical magazines from 2015 to the present" (Maseleno et al., 2018). Our query in the database was limited to SSCI-indexed journal articles, which are the highest-quality studies accessible. Consistent with earlier synthesis studies, we used a 10-year publication window (2007-2017) to provide adequate data for spotting research trends (Lin & Lan, 2015). We categorized articles related to personalized learning under "education/educational research," recognizing that the term is also used in computer science. Our inclusion criteria ensured that each article was relevant to tailored learning and read extensively. Specifically, each article had to relate to technology-assisted customized education and discuss implementing adaptive/personalized teaching and learning activities using e-learning system customizations. After applying these criteria, our analysis included 70 studies on individualization in education, and Fig. 1 depicts the data collection and processing procedures. We excluded the study by Bingham et al. (2018) as it did not directly address the stated purpose of this review, which was focused on using e-learning systems to enable customized functionalities like personalized interfaces and tailored learning paths. Additionally, we identified 17 duplicates that were excluded from the dataset.
Coding Scheme

This study’s coding system, comprised of five primary areas, was designed to explore and assess the changes and trends in customized learning. Xie et al. (2019) suggested utilizing participant-type codes to categorize participants depending on their level of education (Xie et al., 2019). Teacher training and professional development for working people are two separate professions.

Learning content codes

According to the system proposed by Fu and Hwang, the fields of study that can be coded for learning are as follows: engineering/computing; science; health; medical; social science; social studies; arts; languages; mathematics; business and management; other; and unspecified (Fu & Hwang, 2018).

Instructional software and hardware IDs

Pedagogical software and hardware are systemic. Lower-order tailored interfaces, functions, professional learning assistance, prompts/feedback, learning material, learning routes, personalized diagnoses and suggestions, recommendations, prompts/feedback, and learning paths. In this study, nine kinds of instructional materials facilitate customized learning. Hardware codes encompass all customized education equipment. Peng, Ma, & Spector (2019) surveyed the literature on mobile learning and created codes for wearables, smartphones, tablets, and traditional PCs (Peng, Ma, & Spector, 2019).
Learning Outcomes Codes

Emotions, ideas, abilities, actions, relationships, and null experiment results are learning outcome codes. Affection includes technological openness/learning intent, learning attitudes/expectations of learning engagement, learning motivation, self-efficacy/confidence, interest/satisfaction, cognitive load/learning anxiety, and student perspectives/learning experiences (Arias, et al., 2022; Gavilan, et al., 2022). Learning successes, high-order thinking/competence, and teamwork/communication are subgroups of "cognition." The following five groupings are self-contained.

Variable identification codes for individual settings

Customization codes alter pupils' thoughts and feelings during the solo study. Learner profiles comprise achievements, preferences, learning style, cognitive style, learning perceptions, and profiles; courses include lesson plans and student portfolios or logs, and platforms offer technical help. Adaptive/personalized learning uses ten factors. A student's learning perspective includes attitudes, motivation, effort, expectations, self-efficacy, confidence, and satisfaction/interest. Students' viewpoints and emotions during individualized or adaptive training are measured. Students' achievements, preferences, learning styles, cognitive styles, learning perspectives, and profiles. Adaptive/personalized systems employ ten variables (Castillo-Acobo, et al., 2022). A student's unique viewpoint on education depends on how serious they are about learning, how confident they feel in their talents, and how much fun studying is. Several studies have adjusted teaching to students' learning styles; hence "learning style" was utilized as the encoding process. Kirschner's study shows that the idea of a "learning style" is a fallacy (Kirschner, 2017). There have been accusations that empirical findings in learning styles research are limited, issues regarding the reliability of the commonly recognized test, and worries about the absence of a solid association between learning styles and pedagogical techniques (Kirschner, 2017). Three academicians discussed this encoding technique. Two people coded each document. After coding, programmers met with management to resolve inconsistencies. 92% of coding choices were unanimous (Kirschner, 2017). They referred to highlighted areas of the document to explain the coding scores. The management broke up their fights.

Theory framework

This section describes the constructivist theoretical framework. This framework supports the proposed encoding scheme. Piaget's (1960) formalization of constructivism stresses learner-environment interaction and the idea that learners' internal models are built via contact with the external world (Smith, 2017). Piaget's (1960) theory
of cognitive development stresses assimilation and accommodation (Smith, 2017; Paricahua, et al., 2022). "Accommodation" or "assimilation" is adjusting one's mental representation of the world to accommodate new external information (Smith, 2017). This supports the constructivist notion that learning is a process. Abdel-Basset et al. (2019) constructivism in education emphasizes preparation, spiral structure, and invention. "Readiness" refers to "arranging material so it can be absorbed by the learner and providing knowledge in the most effective sequences." In contrast, "spiral organization" refers to "experiences and situations that inspire and competently teach the student (Abdel-Basset et al., 2019)." "Generation," says "education should promote extrapolation and fill gaps" (Abdel-Basset et al., 2019). Fu and Hwang's (2018) research on technology-enhanced learning shows the links between learning support, system characteristics, and learning outcomes (Fu & Hwang, 2018). Individualized teaching on e-learning platforms comes under "learning support." Several colleges let students choose their curriculum or study schedule. It is simple to understand how the encoding approach connects to teaching in the context of personalized learning. Two factors led to the choice to employ constructivism. Both choice theory and this study focus on the learner. According to constructivists, each person's worldview is unique because of their experiences and learning paths (Kampen et al., 2019). As discussed in Section 1, each learner has a unique learning process in personalized learning. Second, constructivism may be used to integrate digital resources like smartphones and the internet (Mamani, et al., 2022). Constructivism offers the theoretical framework for technology-enhanced, individualized learning.

Fig 2. The constructivist theoretical underpinnings of the encoding system
Table 1. Learner Demographics in Personalized Learning Studies

<table>
<thead>
<tr>
<th>Learners Distribution</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elementary School Students</td>
<td>15</td>
<td>21%</td>
</tr>
<tr>
<td>Junior and Senior high School Student</td>
<td>6</td>
<td>9%</td>
</tr>
<tr>
<td>Higher Education Students</td>
<td>32</td>
<td>46%</td>
</tr>
<tr>
<td>Teachers</td>
<td>11</td>
<td>16%</td>
</tr>
<tr>
<td>Working adults</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Others</td>
<td>3</td>
<td>4%</td>
</tr>
<tr>
<td>None</td>
<td>3</td>
<td>4%</td>
</tr>
<tr>
<td>Total</td>
<td>70</td>
<td>100%</td>
</tr>
</tbody>
</table>

Results and discussion

Dispersion of Students

Table 1 shows that most research used college students as subjects. Half the studies utilized these pupils. Second-graders are research participants. High school students are employed as research subjects less commonly than college students. Customized learning studies have equal learner distributions to collaborative mobile learning research (Fu & Hwang, 2018). Working people are not included in this research, despite the majority of the participants. 16% of survey participants are educators, indicating they are receptive to individualized learning (Fu & Hwang, 2018).

Effects of Instructional Variation

Figure 3 shows research article topics, with engineering and computers (n = 17) being the most prevalent. "Others" includes 18 studies. "Others" is not a subject since it includes various topics or a unique concern. Kirschner (2017) employed a context-aware mobile role-playing game to let students explore a game environment and complete goals (Kirschner, 2017). Fu & Hwang (2018) used a web-based strategy to train secondary school teachers on assessment literacy, preparing them to construct a question bank, change test questions, and apply Bloom's taxonomy in student assessment (Fu & Hwang 2018). These studies generally concentrated on science, languages, and math, although engineering/computer was also popular. Medical, nursing, humanities, business, and management are seldom selected in personalized education.
This article studied several systems support forms to understand how they help personalized learning. System support codes include customizable interfaces, learning material, learning routes, diagnoses and suggestions, recommendations, prompts/feedback, professional learning assistance, and other individualized features. Figure 4 shows how bespoke systems may improve learning. 29 of the 70-research used personalized learning material to help students utilize customized approaches. Personalized learning paths for each system user rank second with 17 out of 70 mentions. Personalized interfaces, diagnosis and suggestions, recommendations, and prompts/feedback occur approximately equally often. Low-order customized interfaces and professional learning coaching are underused. Fourteen studies are categorized as extra-tailored functions, such as Chiu and Mok's (2017) exploration of using memory, understanding, and analysis to facilitate adaptive education in secondary-level mathematics classrooms. Figure 6 shows the five research devices used (Chiu & Mok, 2017). "Wearables" are intelligent, wearable electronics. Smartphones run Android, iOS, or Windows mobile. Tablets include the iPad and Android. Traditional computers include PCs, laptops, and PDAs. "Not defined" refers to studies that did not limit their customized systems to one device type. Because of missing hardware information, not all research was included. According to the statistics, most research initiatives employed regular computers or devices to run specialized software.
Fig 4. Various sorts of educational aids and how often they are used

![Learning Support Type](image)

Table 3. The allocation of resources used in customized learning experiments.

<table>
<thead>
<tr>
<th>Hardware Used in research</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wearable devices</td>
<td>0</td>
</tr>
<tr>
<td>Smart phones</td>
<td>4</td>
</tr>
<tr>
<td>Tablet computers</td>
<td>3</td>
</tr>
<tr>
<td>Traditional computers or devices</td>
<td>46</td>
</tr>
<tr>
<td>Not specified</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>59</td>
</tr>
</tbody>
</table>

Learning Outcomes Distribution

Interest, knowledge, competency, conduct, correlations, etc., are learning outcomes. Table 3 shows that student sentiments and understanding are the most prevalent learning outcomes in customized learning trials. 55/70 learning studies assessed emotional and intellectual activity. 3 Digital badges enhanced personalized learning systems for professional progression, according to (Korhonen et al., 2019). Rau et al. (2017) tested these theories by evaluating chemistry students’ collaborative scripts. Their results revealed that visual representation aids problem-solving and teamwork. Developing skills, habits, and connections takes 8.6 to 28.6% of study time (Rau et al., 2017). These studies employed just theoretical or conceptual
models and no experimental data. Affection and intelligence are two of the most studied educational outcomes; thus, understanding their processes is vital. Attachment subcategories include technology openness/learning intent, learning attitudes/anticipation of engaged learning, learning motivation, personal efficacy/confidence, interest/satisfaction, cognitive load/learning anxiety, and student opinion/learning experiences. Figure 5 displays eight categories. Twenty of the 40 studies examined student learning, technology, and satisfaction. One study seldom explored cognitive stress and learning anxiety.

Cognition includes learning outcomes, high-order thinking/competence, and the capacity to collaborate and communicate. Figure 6 shows the classifications. Most assessments measure learning achievements. Student performance improves in 37 of 43 cognitive studies. Seven and four research examines high-order thinking, competence, and cooperating and communicating. Browse the experiment findings by one of several specified categories to better understand their inequality. Figure 10 shows successful, poor, and indifferent learning results across all five categories. "Others" and "No findings" were omitted due to the report's scope. Table 4 shows that the overall number of results is greater than the number comprising affection/cognition. Table 7 employs 100% stacked bars to present the data because of subcategory sensitivity. Individualized training increases participant satisfaction and performance on emotion, cognitive, and behavior surveys. Positive and negative correlation results were about equal. One study found nothing terrible. Liu et al. (2017) studied adaptive learning's impact on students' biology, chemistry, arithmetic, and information literacy expertise. Poorly planned intervention lowered students' tech uptake. Table 7 and 8 illustrate love and cognition testing. Positive, negative, and neutral outcomes are now depicted by absolute stack bars.
Table 4. Affection’s eight subcategories.

<table>
<thead>
<tr>
<th>Affection’s eight subcategories</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology acceptance/ learning intention</td>
<td>22</td>
</tr>
<tr>
<td>Learning motivation</td>
<td>14</td>
</tr>
<tr>
<td>Satisfaction/ interest</td>
<td>17</td>
</tr>
<tr>
<td>Learning anxiety</td>
<td>1</td>
</tr>
<tr>
<td>self-efficacy/confidence</td>
<td>9</td>
</tr>
<tr>
<td>learning attitude/expectation of learning engagement</td>
<td>8</td>
</tr>
<tr>
<td>Cognitive loads</td>
<td>4</td>
</tr>
<tr>
<td>Opinions/learning experiences of students</td>
<td>17</td>
</tr>
</tbody>
</table>
Fig 6. Cognitive subcategories

Table 6. Positive, negative, and mixed learning results

<table>
<thead>
<tr>
<th>Learning results</th>
<th>Positive</th>
<th>Negative</th>
<th>Mixed Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>7</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Skills</td>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Behavior</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Affection</td>
<td>85</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Cognitions</td>
<td>43</td>
<td>0</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 7. Positive, adverse, and mixed affection outcomes

<table>
<thead>
<tr>
<th>Affection outcomes</th>
<th>Positive</th>
<th>Negative</th>
<th>Mixed Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opinions/Learning experiences of students</td>
<td>12</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Cognitive locals</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Learning anxiety</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>satisfaction/interest</td>
<td>17</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Self-efficacy/confidence</td>
<td>8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>learning motivation</td>
<td>12</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>learning attitude/expectation of learning engagement</td>
<td>8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>technology acceptance/learning intention</td>
<td>21</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 8. Positive, negative, and mixed cognitive outcomes

<table>
<thead>
<tr>
<th>Cognitive outcomes</th>
<th>Positive</th>
<th>Negative</th>
<th>Mixed Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning achievement</td>
<td>32</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Collaboration/Communication</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Higher order thinking/Competence</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 9. Distribution of three learning perception subcategories

<table>
<thead>
<tr>
<th>Distribution of three learning perception subcategories</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfaction/Interest</td>
<td>4</td>
</tr>
<tr>
<td>Self-efficacy/Self-confidence</td>
<td>3</td>
</tr>
<tr>
<td>Learning attitude/learning motivation/high expectations</td>
<td>7</td>
</tr>
</tbody>
</table>

Discussion

Learner-Related Research Issues

No working persons participated in the research, per paragraph 5.1. Individualized learning generally takes longer than other kinds of classes. Researchers find it challenging to integrate working individuals in a control/experimental environment and assure their knowledge equality.

Hardware configurations utilized to give individualized/adaptive training may also be a factor. Ordinary computers powered most
bespoke systems. Workplace smartphones may not be compatible. If the UI is not responsive, it may not work on smartphones and tablets (Smutn, 2012). Working people are more challenging to engage throughout the learning process than university students or instructors, who may meet more often with the study team. If future research concentrates on workers, it will be more feasible to build web-based, portable solutions like smartphones or wearables. Take Huang et al. (2016)'s context-aware and mobile and customized language-learning system developed to enhance productivity (Huang et al., 2016). The study suggested that the future workforce will be recruited as research subjects when the price of customized mobile or wearable systems drops.

Content-learning-related research concerns

Engineering/computer and others, science, languages, and mathematics are most typically utilized in these analyses. In contrast, health, medical/nursing, social science/studies, art/design, business, and management are less often used. These disciplines are widely addressed in elementary and secondary school, and researchers usually have the domain knowledge and skills to understand their uses fully. If they did not study medicine, nursing, social science, art, or business in college, they are less likely to have job skills in these fields. Without subject knowledge, it is challenging to deliver adaptive or personalized learning. Individualized education across topics is vital. Adapting learning approaches to individual requirements is one possibility. Lin and Lin (2016) proposed a mobile interactive learning and diagnostic system that can handle adaptive learning if each nurse’s learning procedures are recorded (Lin & Lin, 2016). To assist academics in understanding the structure of domain knowledge in various disciplines and organize the learning content of adaptive/personalized systems, an emerging trend is to automatically extract the knowledge structure using deep neural networks to create knowledge graphs (Shi & Weninger, 2017).

Hardware-related research concerns

Section 5.3 notes that traditional computers are preferred for adaptive and personalized learning systems. Most adaptive and customized systems were constructed utilizing existing systems and development packages for ordinary computers and gadgets to save time and effort (Patterson & Erturk, 2015). Custom wearable systems are unavailable because university researchers lack the necessary IT skills and understanding. Advances in IT for mobile and wearable devices will integrate adaptive/personalized learning systems. Wearable personal learning technology may gather data from the user or surroundings to enhance educational techniques like differentiation and student
engagement. Wearable learning systems that capture individual data will become mainstream.

Examining issues of systemic support and learning outcomes

Section 3.4 notes that higher-level thinking and communication skills are frequently disregarded in favor of academic achievements. Academic achievements are more straightforward to measure than critical thinking and communication. Mavroudi et al. (2016) established essential success criteria for assessing students' higher-order thinking in a teacher-designed, adaptive learning scenario (Mavroudi et al., 2016). The study employed fuzzy set and crisp set QCA. Due to the intricacy of the computation and data collection technique, which requires human data input from users and research team members, the assessment approach cannot be scaled up (Mavroudi et al., 2016). Section 5.3’s examination of system support offers another cause. In personalized systems, the individualized study material is most important. Since this learning support focuses on learning outcomes, it will not aid with higher-order thinking and communication. With the rise of collaborative and immersive learning environments facilitated by virtual reality, we expect more studies on higher-order thinking and communication in personalized learning systems (Greenwald, Corning & Mae, 2017).

Theoretical gaps

Sections 4.3’s theoretical foundation and 5’s statistics data may help us identify research requirements. The spiral comprises two components. First, the information must be understandable. Second, “material must be sequenced.” Personalized systems use spiral parameters and support types. Fig. 14 displays structural and sequencing research. Twenty-nine studies relate to personalized learning material’s structure, while 17 study personalized routes’ sequence. (Chen et al., 2016) integrates individualized learning materials and routes. Few studies examine spiral organization as a whole, focusing instead on structure or sequencing. Second, education should emphasize experiences that make pupils enthusiastic and capable of studying. Learning perceptions reflect readiness. Many studies have sought to enhance learning using human input or system records, but data sources are restricted. Bond & Bedenlier (2019) offered an adaptive learning system, including student profiles, learning styles, etc. (Bond & Bedenlier, 2019). Lin & Lin (2016) designed a customized creative learning system to give personalized learning paths by accessing abundant data sources, including user profile data and questionnaire answers throughout learning (Lin & Lin 2016). Widespread techniques acquire context-aware user data for personalized services. Real-time adaptive/personalized learning requires integrating these tactics into technology-enhanced learning.
From our theoretical framework, the absence of data-gathering tactics in technology-enhanced learning hinders teaching based on learners' experiences and environments.

Conclusion
Technology in education research focuses on personalized learning. This analysis of relevant studies published between 2002 and 2017 discusses implementation settings, learning tools, learning objectives, study participants, and hardware devices. Constructivism promotes methodical encoding. A comprehensive look into statistical coding subsets. Chen et al. found that gender, cognitive style, and baseline knowledge affect students' reactions to customized vs. no personalized learning settings (Chen et al., 2016). Female pupils fared better with individualized learning than with non-personalized (Chen et al., 2016). According to Bingham et al. (2018), tailored lectures may be more successful when they include students' preferred learning techniques (Bingham et al., 2018). Adaptive, customized education requires field-specific learning theories. Chen et al. (2016) employed item-response theories and learning memory cycles to teach English vocabulary. In a follow-up study on personalized vocabulary education, researchers employed situational learning theory to test if mobile device data may help students acquire idioms (Chen et al., 2016). It highlighted researchers' problems and predicted improvement. According to the results and debate, personalized learning systems may soon prioritize adult learners. Mobile or wearable technology that offers tailored solutions will boost student engagement. IT for learning apps on mobile and wearable devices will usher in a new era of "wearable personal learning" (Borthwick et al., 2015) to enhance lesson preparation, personalization, and student engagement. Knowledge graph approaches in AI (Shi & Weninger, 2017) and individual learning data will assist customized medical, sociology, and social sciences systems. Few resources have been devoted to higher-order cognitive and communication skills when addressing learning outcomes and tailored training. Virtual reality technologies that foster collaborative and immersive learning will soon present the potential for adaptive and customizable systems to enhance higher-order thinking and communication. This lecture examines trends and problems in adaptive/personalized technology-supported learning. AI, VR, cloud computing, and wearable computing will allow a wide variety of future applications, such as wearable personal learning technologies, collaborative and immersive personalized learning, etc. The present research analyzed trends and advancements in technology-enhanced individualized learning quantitatively.
Bibliography


414


