Design a Data Analytics Training System to Explore Behavioral Intention and Immersion for Internal Enterprise Education

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ABSTRACT

This research delves into the integration of the CDIO framework and gamified learning into a web crawling system, aiming to elevate the innovation and practical skills of corporate trainees. The study examines the effects on learning achievement, immersion, and behavioral intentions among corporate trainees. Results indicate that those utilizing the gamified web crawling learning system exhibit enhanced learning achievement. HMSAM analysis unveils notable standardized path coefficients, wherein perceived ease of use positively influences perceived usefulness, curiosity, joy, and control. Perceived usefulness and joy significantly impact behavioral intention to use, prompting corporate trainees to express a continued willingness to use the system. These findings deepen our comprehension of CDIO and gamified learning applications in corporate education and training, emphasizing the importance of aligning educational tools with the interests and preferences of corporate trainees.

KEYWORDS

Behavioral intention, Data Analytics, End User Computing, Hedonic-Motivation System Adoption Model, Human Machine Interface, Internal Enterprise System, User Interface, Virtual Desktop Infrastructure

The development of artificial intelligence has attracted global attention. The emergence of big data, machine learning, deep learning, and cloud computing allows engineers to create machines that simulate human intelligence. Artificial intelligence is considered an indispensable driving force for the fourth industrial revolution and may lead to the fourth education revolution (Zhai et al., 2021). In recent years the number of studies exploring the application of AI in various fields has steadily increased. One such study is that of Maican et al. (2023), which investigated the intention to use AI for generating images in a business context, a topic which includes questions of human-computer

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interaction. Li et al. (2023) summarized the elements that impact consumers' confidence in AI chatbots, categorizing them as factors associated with AI chatbot interactions. Numerous studies have explored the opportunities for applying AI in education; Du Boulay (2016) mentioned the development of an intelligent tutoring system through AI to establish personalized learning environments for trainees. The integration of AI into formal school curricula is also becoming a reality (Chen et al., 2023; Dai et al., 2020; Knox, 2020). To better align trainees with AI in their learning processes and future careers, it is essential to start designing and implementing relevant courses from the foundational level (Renz & Hilbig, 2020). However, most AI-related courses are currently offered at the higher education level, making it particularly important to design courses that are engaging and appealing to corporate trainees.

The CDIO (Conceive, Design, Implement, Operate) teaching model is designed primarily to equip engineers with the skills required in the 21st century to meet current industrial demands (O'Connor et al., 2023). The CDIO framework is used to enable trainees to actively construct knowledge and innovate, thereby enhancing their skills and knowledge (Crawley et al., 2007). It emphasizes the content that trainees need to learn (Edström & Kolmos, 2014). CDIO has been applied in various research areas, such as engineering education (Martin & Wackerlin, 2016), geology (De León, 2014) mass communication (Tangkijviwat et al., 2018), and architectural education (Nyka et al., 2020). In addition, the CDIO teaching model can be integrated into learning activities to enhance high-order thinking, Julius Fusic et al. (2022) designed an experiment to verify whether the CDIO model can achieve analytical and evaluation cognitive levels in mechatronics engineering learning activities. The results showed that students using the CDIO framework are better than other students at acquiring higher-order thinking skills. Therefore, the current study integrates the CDIO model into gamified learning, leveraging its appeal to guide corporate trainees in implementing the learning content actively.

Gamified learning creates learning scenarios that provide players with opportunities to learn specific topics and content (Prensky, 2003). A learning environment that combines education and games is primarily designed to allow trainees to achieve a sense of accomplishment through challenges and problem-solving set within a game. This environment enhances students' learning motivation and effectiveness while cultivating their ability to independently create knowledge (Tokac et al., 2019; Zainuddin et al., 2020). The gamified environment can improve learning outcomes, as trainees maintain a high level of interest, fun, and engagement throughout the process (Garris et al., 2002). This finding aligns with other demonstrated benefits of gamified learning, such as improved academic performance (Grivokostopoulou et al., 2019) and higher levels of learning interest and motivation (Bhandari et al., 2019; Chang et al., 2020). Gamified learning has been widely applied in various fields and disciplines, integrating various teaching theories (Zainuddin et al., 2020), two-tier testing (Hwang et al., 2023), self-determination theory (Jones et al., 2022), prediction-observation-explanation learning strategy(Yang & Chen, 2023), among others.

On the basis of the above research, this study integrates a CDIO framework with a gamified learning design platform in AI education. AI focuses on the design and principles of rational agents (Rusell & Norvig, 2003), and data mining systems are excellent examples of rational agents. Data mining is also used in most AI applications, such as reasoning, planning, natural language processing, and robotics (Wu, 2004). This study uses a data analytics course as the learning content, called web crawler, transforming the logical concepts of data definition and collection in data mining—including Python programming and hypertext markup language concepts—into interactive gamified teaching materials. Through a hedonic motivation system, the study aims to understand corporate trainees' immersion and intention to use the data analysis learning system. The objectives of this research are as follows:

1. Establish a web crawler learning system based on the CDIO framework combined with gamified learning.

2. Explore the learning effectiveness of the web crawler learning system.
3. Investigate the immersion and behavioral intention of using the web crawler learning system.

LITERATURE REVIEW

Web Crawlers

Web crawler refers to a program or script that systematically and automatically browses websites (Kausar et al., 2013; Lawson, 2015). With the widespread use of the internet in recent years, it has provided people with vast amounts of information, often in unstructured form (Sirisuriya, 2015), making the task of finding relevant and valuable information time-consuming. Therefore, the ability to automatically discover valuable information from the web has been developed as a response to information overload (Lu et al., 2017). Through web crawlers, it becomes possible to quickly locate interesting content in this vast and complex internet landscape without manually searching websites (Hillen, 2019).

The application of web crawlers in various fields is not uncommon (Khder, 2021). The data collected through web crawling not only saves time but also lays the foundation for a significant amount of basic data for data mining (Bar-Ilan, 2001; Thelwall, 2001). This allows for more in-depth analysis and information applications, such as market analysis, price comparison, trend analysis, and more (García-Mendoza & Juárez Gambino, 2022; Gendreau et al., 2022; Lee et al., 2023; Lu et al., 2017). Data mining has become a popular contemporary topic, and to better cope with this scenario, enhancing awareness and skills in web crawling is particularly important. Therefore, this study will use air quality indicators, Taiwan Bank exchange rates, weather forecasts, and real-time weather as data collection targets.

The CDIO Teaching Approach

The CDIO model advocates for an experiential-based educational approach, serving as a method to promote active and participatory learning. It is also an international collaboration aimed at developing and improving engineering education (Crawley et al., 2014). In contrast to traditional passive teaching, the CDIO approach emphasizes collaborative learning and trainee-led initiatives, increasing the workload on trainees. This may potentially reduce trainees' enthusiasm and lead to negative evaluations of teaching, discouraging instructors from reforming their teaching methods (Ryan et al.,1980; Gutwillwise, 2001).

The CDIO initiative began in 2000, with the initial participation of three universities in Sweden and the Massachusetts Institute of Technology in the United States. Since then an increasing number of universities have joined the CDIO program, making it a leading engineering education model in North America, Europe, and Asia (Dym et al., 2001, 2009; Wesner, 2006). In recent years, the CDIO approach has been introduced into engineering-related fields such as power electronics (Hren et al., 2012), aerospace engineering (Padfield, 2006), and computer engineering (Carvajal et al., 2010). The CDIO initiative is built on three key concepts: a vision, a syllabus, and twelve standards. The CDIO vision aims to provide trainees with a comprehensive education, emphasizing a foundational knowledge set within the context of conceiving, designing, implementing, and operating real-world systems and products (Crawley et al., 2008). The CDIO syllabus details the essential knowledge, personal abilities, interpersonal skills, and CDIO capabilities that trainees should possess upon leaving the university (Bankel et al., 2003).

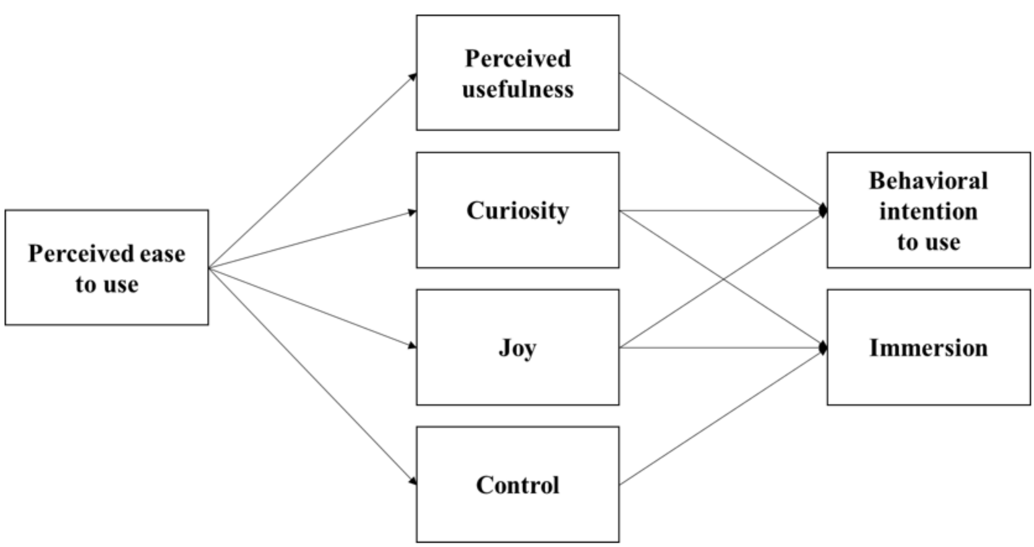
The CDIO standards provide systematic guidance for the implementation and assessment of the entire model, holding significant instructional value for both trainees and instructors (Malmqvist, 2006). The CDIO model emphasizes the significance of project processes (Powell & Kalina, 2009), encouraging trainees to contemplate and practice throughout the entire course (Max et al., 2009). Within the CDIO framework, instructional activities integrate real-world production into specific projects, with teams of trainees assigned specific tasks to work on collaboratively. To achieve their goals, trainees must skillfully design the entire process, including methods, procedures, and even predictions of potential scenarios (Berggren et al., 2003). At the conclusion of the project, the team compiles a final report demonstrating how they addressed problems through collaboration or communication and providing feasibility recommendations. Following project implementation, trainees' problem solving skills (such as personal abilities and teamwork) and knowledge (such as interdisciplinary integration) are correspondingly enhanced (Padfield, 2006; Gu et al., 2008). Additionally, the CDIO model has a positive impact on instructor development. The program offers CDIO support to instructors, enhancing not only their abilities in personal and interpersonal relationship skills developed in professional practice but also their capabilities in integrated learning experiences, active and experiential learning, and the assessment of corporate trainees' learning.

The Hedonic Motivation System Adoption Model

The hedonic-motivation system adoption model(HMSAM) originates from the technology acceptance model proposed by Davis (1985) and integrates user attitudes and flow experiences with the system. This model also emphasizes positive attitudes, such as perceived usefulness and perceived ease of use, enhancing behavioral intention and certain cognitive abilities. The improvement in cognitive abilities also influences behavioral intention (Lowry et al., 2012), as illustrated in the model structure shown in Figure 1.

The framework of the HMSAM focuses primarily on the impact of users' intrinsic motivation during the experience, especially in online gaming, virtual worlds, social networks, and gamified learning environments (Oluwajana et al., 2019). Nikou and Economides (2014) proposed that maintaining intrinsic motivation is one way to make trainees more likely to sustain engagement in programming courses. Krugel and Ruf (2020) pointed out that visual programming environments can generate high intrinsic motivation in trainees, leading to better learning outcomes. Therefore, this study, based on the HMSAM, seeks to understand changes in trainees' intrinsic motivation and behavioral intentions after using the system.

Figure 1. Hedonic-motivation system adoption model (Lowry et al., 2012)



METHOD

In the realm of corporate training and AI education, the quest for effective learning methods is a perpetual endeavor. This study positions itself at the intersection of innovation and education, aiming to evaluate the effectiveness of a novel learning approach. The approach in question involves the construction of a data analysis learning system—a synthesis of the CDIO framework and gamified learning elements. Through a comprehensive experiment, the study delved into corporate trainees' learning outcomes, their immersion in the learning process, and their behavioral intentions following this innovative learning approach. The focal point of this educational intervention was a course titled "Introduction to Data Analysis." Nestled within the broader context of AI education, this course strategically focused on data mining—a pivotal aspect of contemporary data analysis. The primary objective was clear: to equip corporate trainees with practical skills in applying programming languages and understanding hypertext markup language concepts within the context of data analysis.

The strategic alignment of the course content with real-world applications emphasized a commitment to the CDIO framework. The CDIO framework's essence lies in its systematic approach, guiding learners through the Conceive, Design, Implement, and Operate phases. This approach ensures a holistic understanding of the subject matter, transcending theoretical understanding and moving into practical application—thus following a key tenet of effective education. The learning system's integration with gamified elements introduces a dynamic layer to the educational experience. Gamification, grounded in motivational psychology and user engagement theories, holds the potential to transform the learning landscape. By infusing gamelike elements into the educational context, the study aimed to enhance not only knowledge acquisition but also the overall engagement and motivation of corporate trainees.

As the experiment unfolded, the study turned its lens toward assessing corporate trainees' learning outcomes—a multifaceted exploration that went beyond traditional assessments. The focus on programming languages and hypertext markup language concepts reflected the evolving demands placed on professionals in the AI and data analysis domain. Corporate trainees, tasked with compiling programs based on problem requirements and objectives, engaged in a hands-on exploration of the intricacies of data collection, nurturing logical programming skills in the process. The integration of gamified elements within the learning system set the stage for an immersive and engaging learning experience. Immersion, in the context of this study, went beyond mere participation—it meant that trainees were deeply absorbed and focused on the learning activities. The gamified elements served as catalysts, sparking curiosity and imagination and fostering a sense of joy and enjoyment in the learning process. These elements contributed to the creation of a learning environment where trainees felt a high degree of freedom and control over their educational journey.

As the landscape of educational environments evolves, the CDIO framework emerges as a beacon, guiding the integration of theoretical frameworks into practical applications. The study's emphasis on aligning the CDIO framework with the unique needs and preferences of corporate trainees resonates with the user-centric design principles within the broader landscape of educational research. The acknowledgment that curriculum materials, functionalities, and course content must establish meaningful connections with trainees ensures a tailored and responsive educational philosophy. The study contributes not only to the effectiveness of this innovative learning approach within the specific context of corporate training but also to the broader discourse on pedagogical innovation in AI education. By exploring the impact of integrating the CDIO framework and gamified elements, the study adds valuable insights to the evolving landscape of educational methodologies. Therefore, this study's journey from the construction of a data analysis learning system to the assessment of corporate trainees' learning outcomes, immersion, and behavioral intentions is a testament to the dynamic nature of contemporary education. Grounded in the CDIO framework and enriched with gamified elements, this learning approach seeks to bridge the gap between theory and practice, engaging corporate trainees in a holistic and immersive educational experience. As educational environments continue to embrace innovation, this study provides significant illumination of the path toward effective and engaging learning methodologies in the realm of AI education.

Experimental Procedure

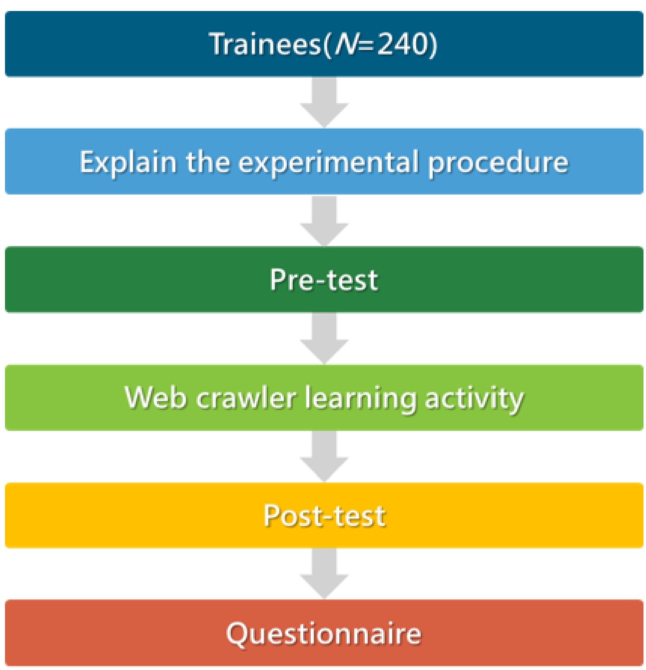
In this study, a cohort of 240 new corporate trainees, averaging 25 years of age, was selected as participants. Ensuring informed consent, researchers verified that all trainees demonstrated a comprehensive understanding of its objectives and joined the experiment voluntarily. The experimental procedure, as illustrated in Figure 2, involved several steps. The experimental process initiated with a 40-minute pre-test phase, evaluating participants' baseline data analysis knowledge. This step aimed to gauge the disparities between pre-test and post-test scores, serving as a crucial metric for assessing the efficacy of the corporate trainee learning system. Subsequently, the participants immersed themselves in a four-week web crawling application learning activity facilitated by the data analysis learning system.

Upon completion of the learning activity, a post-test was administered to measure the knowledge enhancement achieved during the program. Additionally, participants were tasked with completing the HMSAM questionnaire, an integral component, lasting one hour. This questionnaire delved into various aspects related to the learning experience, providing valuable insights into the effectiveness and impact of the employed instructional approach. This study ensured a robust methodology for evaluating the corporate trainee learning system. The combination of pre-tests, learning activities, post-tests, and comprehensive questionnaires contributed to a holistic understanding of the participants' learning journey, facilitating meaningful conclusions.

System Design

This study unveiled a cutting-edge web crawling learning system meticulously designed to impart data analysis skills and delve into the intricacies of the system architecture, its functionalities, and

Figure 2. Experimental procedure



the pedagogical considerations that underscore its development. The learning content of the web crawling system was strategically centered around data analysis—a critical skill set in the contemporary landscape. A noteworthy aspect of the system's design was the conscientious collaboration with experts and the incorporation of instructor input to meet the requirements of the Introduction to Data Analysis course. The system architecture was bifurcated into the instructor's end and the trainee's end, ensuring a comprehensive and tailored learning experience. At the instructor's end, a multifaceted array of features empowered instructors to curate and manage the learning journey. The instructor's end included

a) E-Portfolio: Instructors could edit and manage information for all trainees participating in the Introduction to Data Analysis course.
b) Challenge Bank: Instructors could add, modify, and delete topics related to data analysis applications, all of which were AIoT-related. Topics included air quality indicators, Taiwan Bank exchange rates, weather forecasts, and real-time weather.
c) Material Bank: Instructors could adjust the difficulty of learning content on the basis of trainees' learning conditions.
d) Learning Status: Instructors could understand trainees' learning progress, task completion progress, and relevant information about their learning journey.

On the trainee's end, the functionalities were equally robust, promoting active engagement and skill development. The trainees' end included

a) Coding Practice: Trainees could practice implementing Python syntax and web crawling-related libraries.
b) AIoT Challenges: Trainees worked on the data collection of AioT, and the collected data would be presented on the data analysis dashboard.
c) Quiz: Trainees could practice exercises on grammatical concepts.
d) Learning Materials: Concepts of basic Python programming syntax and web crawling-related libraries.

Figure 3 vividly illustrates the functionality of the web crawling learning system, providing a visual roadmap for its intricate architecture. Figure 4, showcasing screenshots of the learning system, offers a glimpse into the user interface, emphasizing the user-centric design. It is clear that the web crawling learning system presented in this study exemplified a harmonious blend of pedagogical innovation, technological sophistication, and user-centric design. The collaborative development process, the instructor and expert input, and the dynamic functionalities underscore the study's adherence to the principles of robust methodologies, diverse perspectives, and comprehensive understanding. As educational landscapes evolve, this study sets a precedent for the integration of cutting-edge technologies and pedagogical strategies, offering a blueprint for fostering effective data analysis skills among corporate trainees.

The integration of the CDIO instructional model into the design of the web crawling learning system signifies a thoughtful alignment with educational best practices. This pedagogical framework, which emphasizes the processes of conceiving, designing, implementing, and operating, is encapsulated in Figure 5. This study scrutinized the intricate connections between the CDIO processes and Bloom's cognitive domain educational goals, underscoring the theoretical underpinnings that inform the system's design. The CDIO framework, as applied in this study, aligns with Bloom's cognitive domain educational goals across various dimensions of learning. The conceiving aspect, synonymous with the cognitive domains of memory and understanding, was operationalized through specific components. Definition questions prompted trainees to delve deeply into the motivation, background, and data

Figure 3. System structure (a) Quiz (b) AIoT challenges

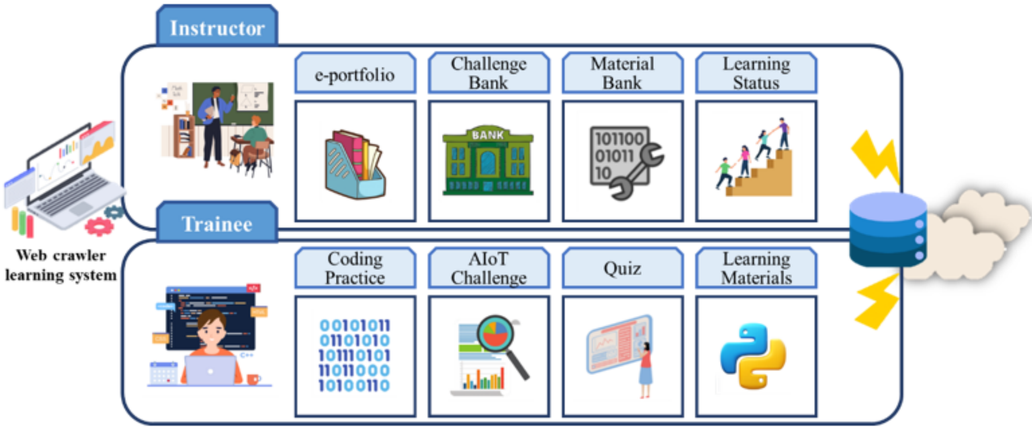
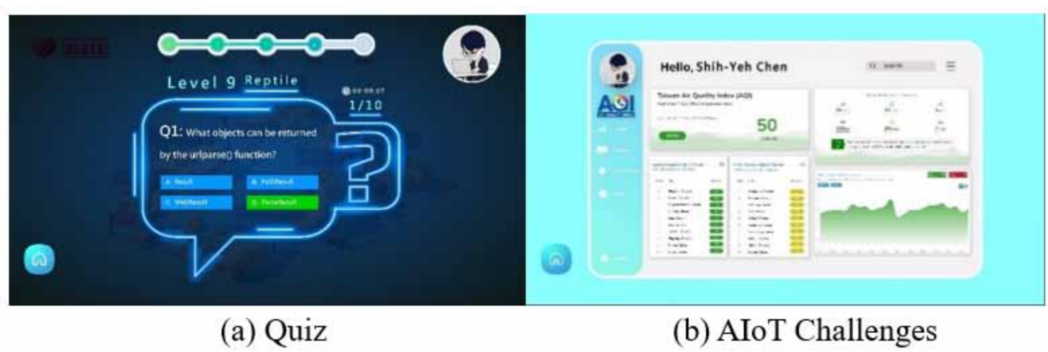


Figure 4. A snapshot of the system



content necessary to solve problems. This strategic approach not only fostered a comprehensive understanding of the subject matter but also cultivated critical thinking skills. These skills include

a) Definition questions: Guiding trainees to deeply contemplate the motivation, background, and data content necessary to solve problems.
b) Programming skill: Ensuring that trainees grasped basic concepts of writing code and applying libraries in programming languages.
c) Data resource: Confirming the required content and sources of data.

The design aspect aligns with Bloom's cognitive domain educational goals of application, including

a) API connection: Evaluating the suitability of existing open resources.
b) Resource planning: Planning for the required resources to avoid an excessive program load or extensive code content.
c) Design framework: Clearly designing the code into executable blocks for better management and maintenance in the future.

The implementation aspect aligns with Bloom's cognitive domain educational goals of analysis, covering

a) Scientific Foundation Viewpoint: Understanding the importance of data analysis and the relationship between collected data, collecting data for different definitions, and requirements.
b) Knowledge Application Principles: Applying software development skills to collect data.
c) Discussion: Engaging in discussions with peers, testing, improving, and sharing programming and logical aspects.

The operation aspect aligns with Bloom's cognitive domain educational goals of evaluation and creation, including

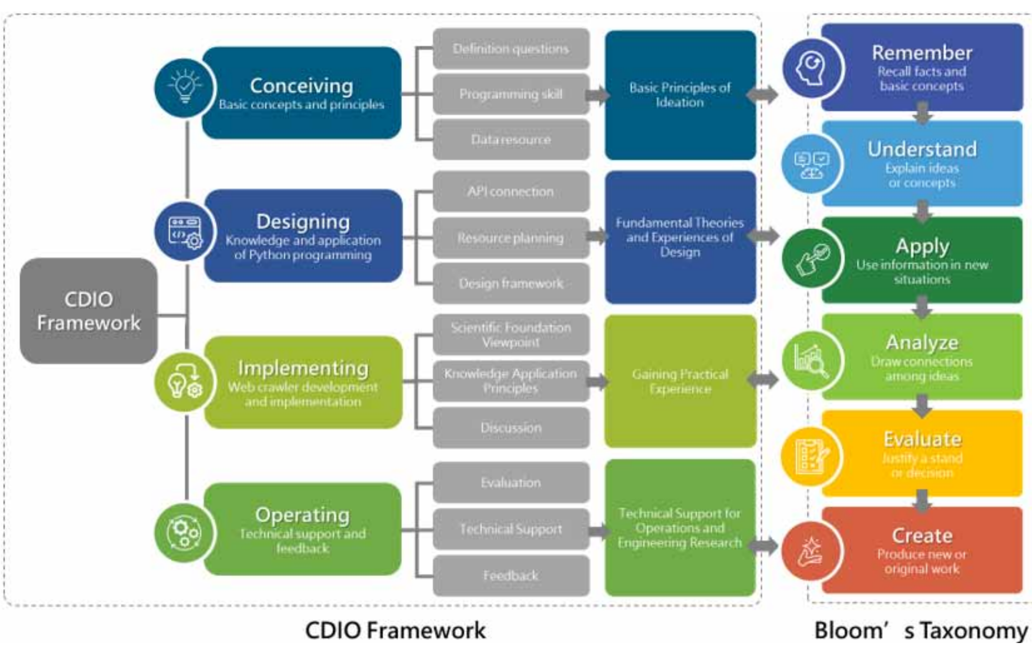
a) Evaluation: Trainees repeatedly tested and corrected program content.
b) Technical Support: Adjusting data content frequency, presentation methods, etc., based on conditional requirements.
c) Feedback: Providing feedback on program content after collecting data for a certain period.

These examples demonstrate that the infusion of the CDIO instructional model into the web crawling learning system design reflected a nuanced understanding of educational psychology and cognitive development. By aligning with Bloom's cognitive domain educational goals, the CDIO framework not only guided trainees through a structured learning journey but also ensured a holistic development of cognitive skills.

Measuring Tools

This study delved into the evaluation of corporate trainees' learning outcomes, immersion, and behavioral intentions following their engagement with a designated learning system, which employed

Figure 5. The CDIO framework in a learning activity



a multifaceted approach, incorporating pre-tests, post-tests, and a detailed questionnaire section. The examination of learning outcomes involved the utilization of pre-tests and post-tests, each comprising 10 basic and 10 advanced questions. These assessments served as pivotal tools in confirming the efficacy of the learning system in enhancing participants' knowledge and skills. To ensure the validity and reliability of these measurement instruments, the content underwent meticulous scrutiny through multiple discussions and revisions. Instructors with expertise in programming courses and experts with relevant educational backgrounds contributed to the refinement process, affirming the content's alignment with the study's objectives. Additionally, the questionnaire section drew on the HMSAM (Lowry et al., 2012), comprising 30 questions on a Likert five-point scale. Table 1 provides valuable insight into the internal consistency of the HMSAM dimensions, as indicated by the Cronbach's α values. Seven dimensions are meticulously examined in the questionnaire: perceived ease of use (PEOU), perceived usefulness (PU), curiosity, joy, control, behavioral intention to use (BIU), and immersion. There are seven items in PEOU, such as "My interaction with the learning system was clear and understandable" and "I found it easy to do what I wanted in the learning system." Its Cronbach's α is 0.843, signifying high reliability. There are five items in PU, such as "The learning system reduces my stress" and "The learning system helps me pass my time better." Its Cronbach's α is 0.946, highlighting its robust reliability. There are three items in Curiosity, such as "This experience sparked my curiosity" and "This experience made me feel curious." Its Cronbach's α is 0.909, indicative of its strong internal consistency. There are three items in Joy, such as "I had a lot of fun playing this game" and "I think it's fun to play this game." Its Cronbach's α is 0.844, attesting to its reliability. There are four items in Control, such as "I have a lot of control when using learning system." and "I have the freedom to choose what I want to see or do." Its Cronbach's α is 0.730. Despite a slightly lower Cronbach's α of 0.730, it still demonstrates acceptable reliability. There are three items in BIU, such as "I plan to use the learning system in the future" and "I plan to continue using the learning in the future", and its Cronbach's α is 0.809, indicating satisfactory reliability. There are four items in Immersion, such as "I was able to tune out most other distractions" and "I'm totally focused on what I'm doing." Its Cronbach's α is 0.880, underscoring its reliability. The reliability value of each aspect of the questionnaire is greater than 0.7, which means it has reliability.

RESULTS

In the pursuit of understanding the impact of learning activities facilitated by a web crawling system based on the CDIO method, this study employed a rigorous statistical analysis. The paired sample t-test emerged as the tool of choice to investigate whether there existed a significant difference between corporate trainees' pre-test and post-test scores. Table 2 encapsulates the outcomes of this analytical endeavor, shedding light on the efficacy of the learning interventions. The statistical analysis revealed

Table 1. Cronbach's α of HMSAM

Dimension	*Cronbach's α*
PEOU	0.843
PU	0.946
Curiosity	0.909
Joy	0.844
Control	0.730
BIU	0.809
Immersion	0.880

a noteworthy finding: there exists a significant difference ($p < 0.05$) in corporate trainees' learning outcomes before and after engaging in the prescribed learning activities. This statistical significance underscores the transformative impact of the web crawling learning system on the participants' understanding and proficiency in data analysis.

Examining the pre-test and post-test scores shows that corporate trainees exhibited a substantial improvement in their average scores after partaking in the learning activities. This improvement serves as a tangible indicator of the effectiveness of the CDIO-based web crawling system in enhancing their grasp of key data analysis principles. The observed enhancement in learning outcomes can be attributed to several factors inherent in the CDIO method. The CDIO approach, rooted in the fundamental principles of Conceive, Design, Implement, and Operate, provides a holistic framework that fosters not only theoretical understanding but also practical application. By engaging in the web crawling learning system, corporate trainees likely experienced a dynamic and immersive learning environment that mirrors real-world data analysis scenarios.

The Conceive phase encouraged a deep understanding of the conceptual foundations of data analysis, laying a robust groundwork for subsequent learning activities. The Design phase enabled trainees to structure their learning experiences, ensuring a coherent and systematic approach to tackling data-related challenges. Implementation, the third phase, translated theoretical knowledge into practical skills through hands-on activities, such as web crawling applications. Finally, the Operate phase ensured that trainees could apply their acquired skills autonomously, promoting a self-sufficient and confident approach to data analysis tasks. The statistically significant improvement in average scores suggests that the CDIO-based learning system effectively bridges the gap between theoretical knowledge and practical application. Corporate trainees not only acquired a theoretical understanding of data analysis concepts but also honed their ability to apply these concepts in real-world scenarios, as evidenced by the post-test scores. Moreover, the use of the Paired Sample t-test added a layer of methodological robustness to the study. By comparing individual trainees' performance before and after the learning activities, the statistical analysis provides a nuanced understanding of the impact on each participant, contributing to the internal validity of the findings.

As these details demonstrate, this study unveils compelling evidence supporting the efficacy of the CDIO-based web crawling learning system in enhancing corporate trainees' learning outcomes in data analysis. The statistical significance of the observed improvements underscores the practical relevance and applicability of the learning interventions, positioning the CDIO method as a valuable framework for imparting data analysis skills in a corporate training context.

The robustness of this study's findings was fortified by a meticulous analysis of construct reliability and convergent validity. This study scrutinized the critical metrics of Composite Reliability (CR) and Average Variance Extracted (AVE). The CR values, exceeding the 0.7 threshold across all constructs, serve as a testament to the internal consistency and reliability of the measured variables. This signifies that the constructs under investigation in this study exhibit a high degree of coherence and reliability, reinforcing the credibility of the study's outcomes.

Simultaneously, the AVE values consistently surpassed 0.5 for each construct, affirming the constructs' robust convergent validity. This metric reflects the extent to which items within a construct converge or measure the same underlying concept. The AVE values, surpassing the recommended threshold, indicate a strong convergent validity, highlighting the constructs' ability to converge around the theoretical constructs they intend to measure. This adherence to the 0.5 criterion underscores

Table 2. Result of learning achievement

	M(SD)		*Df*	*t*	*P*
	Pre-test	**Post-test**			
N=240	64.58(16.831)	76.50(15.918)	239	-7.500	0.046*

the soundness of the measurement model, bolstering the study's validity in capturing the intended theoretical dimensions.

This study placed a deliberate focus on discriminative validity—an essential aspect of construct validation. Discriminative validity endeavors to elucidate the distinctions between constructs, demanding a level of correlation between different facets that underscores their distinctiveness. In pursuit of this goal, the study employed two key analytical indicators: the square root of Average Variance Extracted (AVE) values and the Pearson correlation coefficient. Table 4, a demonstration of the study's commitment to transparency and rigor, reveals the results of discriminative validity analysis.

The square root of AVE values emerges as a pivotal metric, serving as a benchmark for the distinctiveness of each construct. A construct's square root of AVE should exceed its correlation coefficients with other constructs, attesting a level of independence and uniqueness. The meticulous application of this criterion ensures that each facet under scrutiny possesses a distinct identity, minimizing the risk of construct overlap. Crucially, Table 4 communicates a resounding success in achieving discriminative validity in this study. The square roots of AVE values consistently outpace the correlation coefficients with other constructs, attesting to the robust distinctiveness of each facet under investigation.

The results show that the standardized beta coefficient for the path from PEOU to PU is 0.140, with a p-value less than 0.05, meeting the significance standard. The standardized path coefficient from PEOU to Curiosity is 0.213, with a p-value less than 0.01, meeting the significance standard. The standardized path coefficient from PEOU to Joy is 0.153, with a p-value less than 0.05, meeting the significance standard. The standardized path coefficient from PEOU to Control is 0.161, with a p-value less than 0.05, meeting the significance standard. The standardized path coefficient from PU to

Table 3. The CR and AVE

Dimension	*CR*	*AVE*
PEOU	0.8759	0.5041
PU	0.9475	0.7833
Curiosity	0.9188	0.7904
Joy	0.8471	0.6489
Control	0.7991	0.5001
BIU	0.8625	0.6770
Immersion	0.9069	0.7116

Table 4. Correlation and AVE

Constructs	**PEOU**	**PU**	**Curiosity**	**Joy**	**Control**	**BIU**	**Immersion**
PEOU	**0.7100**						
PU	0.179**	**0.8850**					
Curiosity	0.209**	0.216**	**0.8890**				
Joy	0.157*	0.332**	0.208**	**0.8055**			
Control	0.130*	0.128*	0.179**	0.303**	**0.7071**		
BIU	0.136*	0.207**	0.153*	0.218**	0.154*	**0.8228**	
Immersion	0.204**	0.146*	0.238**	0.174**	0.200**	0.209**	**0.8435**

****p<0.001; **p<0.01; *p<0.05*; Square root of AVE on the diagonal.

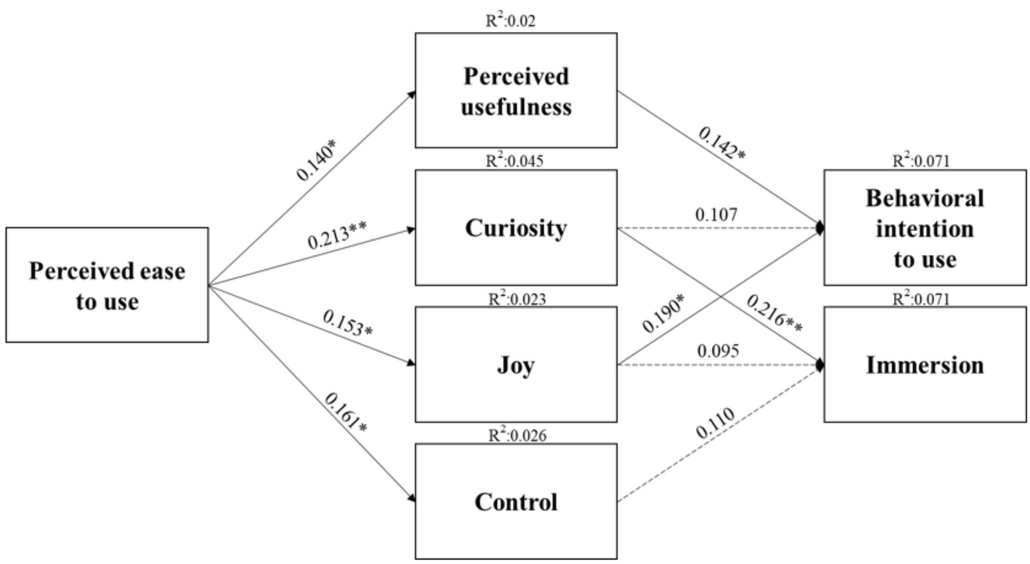
BIU is 0.142, with a p-value less than 0.05, meeting the significance standard. The standardized path coefficient from Curiosity to BIU is 0.107, not meeting the significance standard. The standardized path coefficient from Curiosity to Immersion is 0.216, with a p-value less than 0.01, meeting the significance standard. The standardized path coefficient from Joy to BIU is 0.190, with a p-value less than 0.05, meeting the significance standard. The standardized path coefficient from Joy to Immersion is 0.095, not meeting the significance standard. The standardized path coefficient from Control to Immersion is 0.110, not meeting the significance standard.

DISCUSSION

In the realm of corporate training, the integration of innovative educational philosophies and technologies has become pivotal in fostering the innovative and practical abilities of trainees. This study endeavored to contribute to this landscape by developing a web crawling learning system, seamlessly grounded in the CDIO framework and enriched with gamified learning elements. The multifaceted exploration encompassed not only the learning effectiveness of this novel approach but also delved into the immersive experiences and behavioral intentions of corporate trainees.

The findings of the study reveal a positive correlation between the utilization of the gamified web crawling learning system and enhanced learning effectiveness among trainees. This discovery validates findings from earlier research (Kaya & Ercag, 2023; Lo & Hew, 2020) that demonstrated that the combined use of gamified learning can enhance learning achievement. This finding differs from Alsadoon et al. (2022), who showed that gamification does not affect students' academic performance. The reason for this difference may be that the CDIO teaching method emphasizes the process of conception, design, implementation, and operation, guiding students to carry out learning activities sequentially. This approach is consistent with Bloom's cognitive domain educational goals across various learning dimensions. The practical application of this system facilitates a deeper grasp of key aspects of data collection—a fundamental skill set in the evolving landscape of corporate data analysis. This approach fits the evolving demands

Figure 6. Path analysis model



placed on corporate trainees, highlighting the importance of experiential learning and hands-on application of theoretical concepts.

Additionally, this study investigated the impact of corporate trainees' immersion and usage intentions through HMSAM. The positive significant effect of PEOU on PU suggests that trainees find the system easy to use, requiring less effort in operation, and thus aiding in a better understanding of learning and thinking content. The positive significant effect of PEOU on curiosity indicates that corporate trainees, perceiving the system as easy to use and not requiring significant effort, are triggered in curiosity and imagination. The positive significant effect of PEOU on joy suggests that trainees, finding the system easy to use and not demanding much effort, experience pleasure and find it enjoyable. The positive significant effect of PEOU on control reveals that trainees, considering the system easy to use and not requiring much effort, feel a high degree of freedom in their learning activities, allowing them to control the selection of learning content and progress. This discovery validates findings from Perez et al. (2023) that PEOU yielded positive and significant effects on PU, joy, and control. In this study, unlike Perez et al. (2023), PEOU was found to be significant for curiosity. The reason may be that the purpose of the game was different. This study incorporated a gamified system with learning and training objectives, featuring more task-oriented learning content. Under conditions of ease of use, such a system can stimulate curiosity.

The positive significant effect of PU and joy on BIU suggests that, with assistance in better understanding learning content and a pleasant mood, trainees are willing to continue using the system in the future. This discovery validates findings from Perez et al. (2023) that PU and joy yield positive and significant effects on BIU. Moreover, curiosity has no significant impact on BIU. This may be because the gamified system exists for educational purposes. Although trainees are curious, as long as they have achieved the learning goal, they will not want to continue using it.

The positive significant effect of curiosity on immersion indicates that when trainees generate curiosity and imagination, they become highly focused and immersed in learning activities. This discovery validates findings from Perez et al. (2023) that curiosity yields positive and significant effects on immersion. However, joy and control did not exhibit any significant impact on Immersion. Thus, there is insufficient evidence supporting the relationship between educational gamified systems and immersion.

CONCLUSION

In contemporary times, as an increasing number of educational environments adopt CDIO as an educational philosophy, the primary objective is to foster innovation and practical abilities among corporate trainees. Consequently, in assessing the impact of integrating the CDIO framework with gamified, learning, it is crucial to understand the factors influencing continued usage intention and immersion. This study scrutinized all factors based on HMSAM, involving 240 participants whose responses underwent data validity checks and model verification.

PEOU exhibited the highest effect on curiosity, followed by control, joy, and PU, arranged in descending order of direct impact. This finding underscores the importance of ease of system operation for trainees. Conversely, joy had the most significant impact on BIU, followed by PU, indicating that users prioritize happiness during the process, influencing trainees' continued usage intention. Finally, only curiosity showed a significant effect on immersion, suggesting that thoughtful planning and design of innovative learning content can significantly capture trainees' focus on activities.

The results of this study contribute to a better acceptance of this tool's application in education and training within companies. They also offer insights into the impact of integrating CDIO design. The incorporation of CDIO into design, encompassing curriculum materials, functionalities, and course content, must establish connections with trainees' interests, needs, and preferences. This ensures that trainees can relate to the material, encouraging greater immersion and willingness to actively participate in educational training, thereby enhancing learning outcomes.

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