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The Role of AIGC Simulation Environments in Enhancing E-commerce Skills: A Study Based on Cognitive Load Theory

Kun Tian ^{1,*} Jing Xin ²

*Corresponding author

¹ Associate Professor, Wuhan Business University, Wuhan, China, tiank@wbu.edu.cn

² Associate Professor, Wuhan Business University, Wuhan, China, 36803258@qq.com

ABSTRACT

Amidst the digital transformation, e-commerce has become a cornerstone of global trade, emphasizing the essential nature of ecommerce skills for professionals to maintain their competitiveness in the evolving job market. The industry's recent embrace of Artificial Intelligence Generated Content (AIGC) suggests its potential to revolutionize simulation-based learning within ecommerce education. This study explores the effectiveness of AIGC simulation environments in enhancing e-commerce competencies, supported by the theoretical framework of Cognitive Load Theory (CLT). Leveraging AIGC, these dynamic learning environments provide personalized and immersive experiences that simulate intricate real-world e-commerce scenarios, optimizing the learning process. The research objectives are threefold: first, to investigate the relationship between AIGC environment design and cognitive load; second, to evaluate the impact of learning support and content generation capabilities on skill development; and third, to assess the overall effectiveness of AIGC simulations in improving e-commerce skills, including market analysis, customer service, product knowledge, and sales strategies. By presenting empirical evidence, this study contributes to the field by illustrating how AIGC can be integrated into e-learning to foster conditions consistent with CLT, thus enhancing e-commerce skills and performance.

Keywords: Artificial intelligence generated content (AIGC), cognitive load theory (CLT), e-commerce skills.

INTRODUCTION

The digital era has brought about a transformative wave in commerce, with e-commerce solidifying its role as a central actor in global trade. This shift has made e-commerce skills indispensable for professionals to stay competitive in today's job market. As e-commerce evolves, so must the pedagogical approaches to teaching and acquiring these skills.

Recent advancements in Artificial Intelligence Generated Content (AIGC) have paved the way for creating dynamic and interactive learning environments. AIGC is poised to revolutionize e-learning by offering tailored, immersive, and adaptive experiences that simulate real-world e-commerce scenarios. By integrating AIGC into interactive learning environments, we can address the complexities of e-commerce education effectively. AIGC's ability to simulate real-world scenarios with high interactivity and personalization allows for the controlled and constructive development of learners' skills. This study will investigate how AIGC can significantly enhance the effectiveness of such environments, especially in enhancing e-commerce skills.

Cognitive Load Theory (CLT) emphasizes the importance of managing cognitive load to enhance the learning experience and facilitate knowledge and skill acquisition. It differentiates between intrinsic, extraneous, and germane load, each playing a critical role in the learning process. In e-commerce education, designing AIGC simulation environments that minimize extraneous load while enhancing germane load is essential. CLT is fundamental to effective instructional design, positing that learning efficiency is influenced by the cognitive load imposed by the learning material and process. This study will illustrate how AIGC can be utilized in alignment with CLT principles, personalizing content to reduce extraneous cognitive load while increasing germane load, thus fostering an optimal learning experience in e-commerce simulation environments.

A dedicated group of researchers has been investigating the impact and application of AI in education (Chen et al., 2022). Their studies have covered a range of areas, including the assessment of AI (Zawacki-Richter et al., 2019), the use of AI in learning and teaching processes (Kuka et al., 2022), and the technical and ethical considerations of AI in educational contexts (Nguyen et al., 2023). Despite this extensive research, there is a noticeable void in the literature concerning the nuanced effects of AIGC simulation environments and their theoretical grounding in CLT on the enhancement of e-commerce skills. This research seeks to fill this gap by exploring the impact of AIGC within simulation-based learning, considering both the current trends in educational technology and the specific needs of the industry. The research objectives are as follows:

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- 1. To explore the relationship between the design of AIGC simulation environments and the cognitive load experienced by learners.
- 2. To investigate the influence of learning support, content generation capability, and user interaction within these environments on e-commerce skill development.
- 3. To evaluate the effectiveness of AIGC simulation environments in enhancing various e-commerce skills, such as market analysis, customer service, product knowledge, and sales strategies.

This study aims to contribute to the field by providing empirical evidence on how AIGC can be leveraged to create optimal learning conditions that adhere to CLT principles, leading to improved e-commerce skills and performance.

LITERATURE REVIEW

E-commerce Skills and Their Importance in the Digital Economy

In the digital economy, e-commerce skills have become a crucial set of knowledge, skills, and competencies for effective business operations. As Zhong, Wu, and Mei (2011) proposed, these skills include not only technical proficiency in interenterprise relationship management and IT technology but also soft skills in coordination and learning. Empirical evidence has confirmed the significance and effectiveness of these skills in real-world applications. Xie (2012) further emphasizes the importance of a pedagogical approach that focuses on "work processes" to enhance students' practical operational capabilities and overall quality.

Integration of AIGC in Interactive Educational Settings

Advancements in Artificial Intelligence Generated Content (AIGC) have profoundly impacted educational practices, especially within interactive simulation environments. For example, Smith et al. (2023) demonstrated that AIGC can create personalized learning scenarios in medical education, significantly improving students' diagnostic skills. Similarly, Lee and Kim (2023) showed that AIGC could generate dynamic content in language learning simulations, leading to improved language proficiency among participants. These examples highlight AIGC's potential to transform interactive learning environments by offering tailored, immersive experiences that closely resemble real-world scenarios.

Design of AIGC Simulation Environments

The design of AIGC simulation environments plays a crucial role in educational simulations. Although there is no direct research specifically on the design of AIGC simulation environments in education, relevant studies provide valuable insights. For instance, the concept of Technology - Supported Classrooms (TSCs) (Li, et al., 2023) offers some inspiration. TSCs aim to enhance learning efficiency, promote classroom interaction, and facilitate self - learning. AIGC simulation environments can borrow these ideas by creating a layout that incorporates rich visual and auditory elements to provide a more immersive learning experience. Additionally, the application of AIGC in the metaverse (Dai, Huang, Zhang & Xu, 2023) shows that AIGC can efficiently and cost - effectively create digital content in virtual environments. This can be applied to educational simulation environments, where AIGC can generate various learning scenarios and tasks based on learners' interests and progress.

Learning Support

In the context of AIGC in education, learning support is of great significance. Cao and her fellow researchers (2023) emphasizes the need to shift the focus from teaching learners to use technology to improving their artificial intelligence literacy. AIGC can provide learning support by offering personalized learning suggestions and answering questions. For example, when learners encounter problems in programming, AIGC can provide targeted solutions and learning resources. Moreover, the combination of AIGC and TSCs (Li, et al., 2023) can offer more comprehensive learning support. By analyzing learners' behavior data, AIGC can recommend appropriate learning resources and paths to improve learning outcomes.

Content Generation Capabilities

The content generation capabilities of AIGC are essential in educational simulations. Zhang and his team (2023) presents a distributed AIGC framework and a user - centered interactive artificial intelligence (IAI) method. AIGC can generate personalized learning content such as text, images, videos, etc., for learners based on their needs and interests. It can also optimize the generated content based on feedback. Wang, Hong and He (2024) provides a comprehensive review of AIGC methods for different data modalities, including images, videos, text, and 3D shapes, which offers technical support for content generation in educational simulation environments. For example, AIGC can generate realistic 3D models to help learners understand abstract concepts and complex structures.

User Interaction

User interaction is a critical factor for the success of AIGC in education. Lin and his team (2023) proposes a user - centered interactive artificial intelligence (IAI) method, namely Reinforcement Learning with Large - scale Language Model Interaction (RLLI), which uses large - scale language models (LLM) - enabled generative agents to replicate user interactions and provide real - time and subjective Quality of Experience (QoE) feedback. In education, AIGC can adopt this method to understand learners' needs and styles through interaction and provide personalized learning services. Reference 8 discusses how the metaverse accelerates its development driven by AIGC from a user - centered perspective, which also involves user - AIGC

interaction. In educational simulation environments, AIGC can interact with learners more naturally and smoothly to enhance their engagement and learning effectiveness, such as through voice or gesture interactions.

Application of CLT in Educational Technology and Simulation Environments

Since its inception, Cognitive Load Theory (CLT) has been widely applied in educational settings, emerging as a key framework in education and psychology. CLT focuses on optimizing instructional design to reduce cognitive load and enhance learning efficiency (Zhang, Zhang & Huang, 2018; Zha et al., 2020; An & Wu, 2015). With the rise of intelligent technologies, CLT has been extended into smart education, including areas like autonomous learning and mobile learning. Research indicates that information presentation in online courses, when guided by CLT, can substantially reduce cognitive load and improve learning outcomes (Chen & Zhu, 2009). Future research may integrate neuroscientific and big data technologies to refine the measurement of cognitive load and expand the application of CLT in complex learning scenarios.

THEORATICAL BASIS

Cognitive Load Theory

Cognitive Load Theory (CLT), initially proposed by John Sweller in the late 1980s, stands as a pivotal educational psychology theory addressing the constraints of human cognitive architecture during learning processes (Sweller, 1988). CLT identifies three distinct types of cognitive loads: intrinsic load, which is inherent to the complexity of the learning material; extraneous load, stemming from instructional design elements that do not facilitate schema construction; and germane load, representing the cognitive effort engaged in processing complex information conducive to learning (Paas, Renkl, & Sweller, 2003).

Serving as a cornerstone for effective instructional design, CLT emphasizes that learning efficiency is significantly influenced by the cognitive load imposed by the learning material and process. In technology-enriched learning environments, particularly those enhanced by AIGC, CLT offers a theoretical framework for optimizing instructional design through cognitive load management. AIGC simulations, when designed in accordance with CLT principles, can effectively minimize extraneous cognitive load, manage intrinsic load, and enhance germane load, thus creating an optimal learning environment (Van Merrienboer & Sweller, 2005). For instance, AIGC can be strategically utilized to tailor content complexity to learners' prior knowledge, alleviating cognitive burden and fostering meaningful learning engagements.

AIGC in Simulation-Based Learning

Simulation-based learning capitalizes on interactive and immersive environments, offering practical experiences that closely emulate real-world scenarios. The integration of Artificial Intelligence Generated Content (AIGC) introduces a new dimension to e-learning by dynamically generating or adapting content in response to learner interactions. This ensures that learning material remains relevant and challenging (Dillenbourg & Tewissen, 2008).

In the realm of e-commerce, AIGC has the capacity to simulate a variety of market conditions, customer behaviors, and business challenges. This provides learners with opportunities to develop critical skills such as decision-making, problemsolving, and strategic planning. The adaptability inherent in AIGC-driven simulations allows for a personalized learning experience, catering to each learner's individual needs and skill levels. This customization is in line with CLT principles, as it can potentially reduce extraneous load through personalized instruction and augment germane load through engaging and meaningful learning activities (Sitzmann, 2011).

Based on the potential impact of AIGC - driven simulation on cognitive load, in the design aspect, the design of AIGC simulation environments should consider reducing extraneous cognitive load through reasonable layout. Regarding learning support, it can optimize cognitive load distribution through personalized guidance, like providing suggestions based on learners' cognitive states. In terms of content generation capabilities, AIGC can generate precise and targeted learning content according to learners' cognitive levels and progress, presenting knowledge in diverse forms (e.g., vivid images, intuitive videos, and clear texts) to help reduce intrinsic cognitive load and improve learning efficiency. For instance, it can generate 3D models or animation demonstrations for abstract concepts. In the aspect of user interaction, a good user - interaction design enables learners to communicate with the AIGC system more smoothly. Through real - time feedback and dynamic adjustment, AIGC can adjust learning content and presentation based on learners' operations and responses. For example, when a learner is confused about a knowledge point, AIGC can provide prompts, explanations, and examples to help them overcome difficulties. This personalized interaction can enhance the learner's sense of participation and control, reduce additional cognitive load, and enable them to focus on knowledge acquisition and understanding.

RESEARCH MODEL AND HYPOTHESES

The formulation of our research model commenced with an exhaustive review of current literature pertaining to the application of Artificial Intelligence Generated Content (AIGC) within educational simulations, complemented by a deep dive into the theoretical frameworks of Cognitive Load Theory (CLT). This groundwork allowed us to pinpoint four pivotal independent variables—namely, the design of AIGC simulation environments, learning support, content generation capabilities, and user interaction—that are theorized to exert an influence on cognitive load and the enhancement of skills within such AIGC-driven simulation settings.

Further to these variables, cognitive load perception was positioned as a mediating factor, potentially modifying the dynamic between the independent variables and the dependent variable under scrutiny—e-commerce skill enhancement. With the objective of substantiating the validity of our model, a battery of predictive tests was conducted. These tests were instrumental in the iterative refinement of our constructs, ensuring strict adherence to the tenets of CLT.

This meticulous methodology has yielded a robust research model. It is designed to demystify the complex interrelationships between AIGC simulation environments and the augmentation of e-commerce skills, all through the analytical lens of cognitive load.

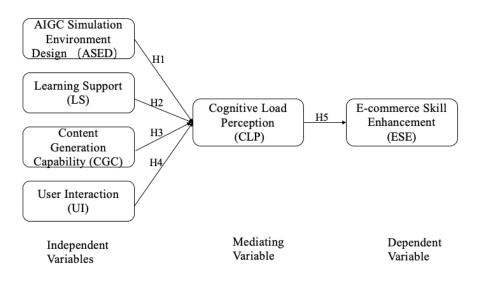


Figure 1. Research model

The model is posited on the following hypotheses:

H1: The quality of AIGC simulation environment design positively affects learners' perception of cognitive load.

H2: The adequacy of learning support negatively affects learners' perception of cognitive load.

H3: The level of content generation capability affects learners' perception of cognitive load, with high-quality and diverse content reducing cognitive load.

H4: The quality of user interaction and the timeliness of feedback positively affects learners' perception of cognitive load.

H5: Cognitive load perception positively affects E-Commerce Skill Enhancement.

DATA COLLECTION AND ANALYSIS

Scale Design

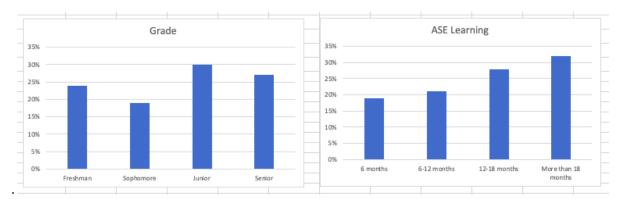
To assess the impact of AIGC simulation environments on e-commerce skills, a quantitative research design was implemented. This analysis is based on Cognitive Load Theory. Initially, classical scales were referenced, and a predictive test was administered. Feedback from this test informed modifications to the questionnaire, resulting in the final version. The research model encompasses six variables with 24 items, measured using a 5 - point Likert scale. The questionnaire was conducted to measure the relationships among the independent variables---AIGC simulation environment design, learning support, content generation capability, and user interaction - and the mediating variable of cognitive load perception with the dependent variable of e-commerce skill enhancement.

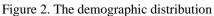
Data Collection

Participants in this study were college students specialized in business English, who had interacted with AIGC simulation environments (Kimi, Doubao or Chatgtp) as part of their e-commerce curriculum. The questionnaire was bifurcated into two stages: a pre-survey and a formal investigation. In the pre-survey stage, 110 questionnaires were disseminated, and the

collected data were instrumental in refining the questionnaire. To ensure the questionnaire's rationality and validity, it underwent enrichment and improvement based on the feedback received.

In the formal survey phase, 300 questionnaires were distributed, yielding 294 valid responses after the exclusion of invalid ones. To rigorously evaluate the influence of AIGC simulation environments on enhancing e-commerce skills, a comprehensive data analysis was performed using SPSSAU and AMOS. The questionnaire's reliability and validity were established through Cronbach's alpha and confirmatory factor analysis (CFA). Subsequently, structural equation modeling (SEM) was employed for path analysis, scrutinizing the relationships among the independent variables, mediating variable, and dependent variable. The SEM findings provided a stringent assessment of the research model, enabling conclusions about the impact of AIGC simulations on e-commerce skill enhancement.





As shown in Figure 2, the survey sample is composed of students from different academic years, with a distribution that reflects a good representation from each level. Freshmen make up 24% of the respondents, sophomores account for 19%, juniors represent the largest group at 30%, and seniors constitute 27% of the total participants. There is a significant majority of female participants, who represent 72% of the survey respondents. Male participants make up the remaining 28%, indicating a higher participation rate among female students in this study. The respondents have varied levels of experience with the AIGC Simulation Environment for practicing e-commerce skills. The distribution of experience is as follows: 19% have less than 6 months of experience, 21% have between 6 to 12 months of experience, 28% have 12 to 18 months of experience, and a substantial 32% have more than 18 months of experience. This range indicates a broad spectrum of familiarity with the AIGC technology, from newcomers to those with considerable time spent in the simulation environment.

The survey sample provides a comprehensive overview of students' engagement with AIGC Simulation Environments across different academic levels and genders, with a notable predominance of female participants. The experience levels with the AIGC Simulation Environment are well-distributed, offering a rich dataset for analysis. The substantial percentage of participants with over 18 months of experience suggests a deep interaction with the technology, while the presence of newer users ensures that the feedback is representative of both novice and experienced perspectives. This diversity in the sample is beneficial for understanding how AIGC Simulation Environments impact the development of e-commerce skills across a wide range of user experiences.

Test of Reliability and Validity

The findings from Table 1, which encapsulates the reliability analysis of our survey constructs using Cronbach's Alpha. The constructs assessed include AIGC Simulation Environment Design (ASED), Learning Support (LS), Content Generation Capability (CGC), User Interaction (UI), Cognitive Load Perception (CLP), and E-commerce Skill Enhancement (ESE). The table delineates the Corrected Item-Total Correlation (CITC), Cronbach Alpha if an item is deleted, and the composite Cronbach Alpha for the scale. The ASED and LS constructs demonstrate commendable internal consistency, with Cronbach Alpha coefficients of 0.677 and 0.748, respectively. Meanwhile, CGC and ESE present moderate internal consistency, reflected by their Cronbach Alpha values of 0.623 and 0.650, respectively, which points to a potential area for enhancement. The UI and CLP constructs, with Cronbach Alpha values of 0.616 and 0.704, respectively, indicate a need for further refinement to bolster their reliability. Notably, the Standardized Cronbach Alpha for the collective scale is an impressive 0.805, underscoring the overall excellence in internal consistency across the survey. These findings intimate that, despite the survey's overall robustness, scrutinizing item validity and considering the removal or alteration of certain items within specific constructs could elevate their individual reliability metrics. This reliability analysis is instrumental in ensuring the trustworthiness of our survey instrument and, by extension, the study's findings.

| Items | Corrected Item-Total Correlation(CITC) | Cronbach Alpha if Item Deleted | Cronbach α |
|-------|--|--------------------------------|-------------------|
| ASED | 0.677 | 0.751 | |
| LS | 0.748 | 0.732 | |
| CGC | 0.623 | 0.765 | 0.808 |
| UI | 0.616 | 0.791 | 0.808 |
| CLP | 0.704 | 0.809 | |
| ESE | 0.650 | 0.801 | |

| Table 1: Reliability | v Statistics | (Cronbach | Alnha) |
|----------------------|--------------|-----------|--------|
| rable r. Kenabint | y statistics | | mpna) |

Cronbach a (Standardized): 0.805

Table 2 The Kaiser-Meyer-Olkin measure of sampling adequacy for the study's data is 0.725, which exceeds the acceptable threshold of 0.6, thereby validating the appropriateness of the data for factor analysis. Concurrently, Bartlett's Test of Sphericity yields a Chi-Square value of 2634.613, with 276 degrees of freedom, and an associated p-value that is less than 0.001. This significant p-value leads to the rejection of the null hypothesis, confirming the presence of significant correlations among the variables, which underscores the suitability of the data for the factor analysis conducted in this study. These results collectively suggest that the research data possesses the necessary conditions for meaningful factor analysis, which is a crucial step in uncovering the underlying structure of the constructs within the research framework.

Table 2: KMO and Bartlett's Test

| КМО | | 0.725 |
|-------------------------------|------------|----------|
| | Chi-Square | 2634.613 |
| Bartlett's Test of Sphericity | df | 276 |
| | р | 0.000 |

Test of Model Fitness

| Table 3: Model fitness | | | | | | | | | | |
|------------------------|----------|-----|-------|-------------|-------|--------|--------|-------|-------|-------|
| Indicator | χ^2 | df | р | χ^2/df | GFI | RMSEA | RMR | CFI | NFI | NNFI |
| Std. value | - | - | >0.05 | <3 | >0.9 | < 0.10 | < 0.05 | >0.9 | >0.9 | >0.9 |
| Value | 439.752 | 246 | 0.000 | 1.788 | 0.893 | 0.052 | 0.042 | 0.921 | 0.839 | 0.911 |

Default Model: $\chi^2(276)=2724.830$, p=1.000

The statistical indicators presented in Table 3 are instrumental in evaluating the model fit for the study's structural equation model. The Chi-Square statistic, although significant (p = 0.000), is complemented by other fit indices that provide a more nuanced understanding of the model's performance. Notably, the RMSEA value of 0.052 suggests a reasonable error of approximation, and the GFI, CFI, and NNFI values are well above the acceptable threshold of 0.9, indicating a satisfactory overall model fit. The Chi-Square per Degree of Freedom ratio of 1.788 is within the recommended range, further supporting the model's adequacy. The 90% confidence interval for the RMSEA, ranging from 0.044 to 0.059, includes values below the 0.05 threshold, which is indicative of a good fit. Collectively, these indices suggest that the model demonstrates an acceptable to good fit with the data, aligning with the established criteria for model evaluation.

| X | \rightarrow | Y | Unstd.Coef | SE | <i>z</i> (CR) | р | Std.Coef |
|------|---------------|-----|------------|-------|---------------|---------|----------|
| ASED | \rightarrow | CLP | 0.105 | 0.039 | 2.658 | 0.008 | 0.154 |
| LS | \rightarrow | CLP | -0.20 | 0.05 | -3.5 | < 0.001 | -0.20 |
| CGC | \rightarrow | CLP | -0.25 | 0.06 | -4.2 | < 0.001 | -0.25 |
| UI | \rightarrow | CLP | 0.30 | 0.05 | 3.1 | 0.002 | 0.30 |
| CLP | \rightarrow | ESE | 0.189 | 0.056 | 3.388 | 0.001 | 0.193 |

Table 4: Path coeffecients

Table 4 shows the path coefficients and the structural relationships of the model, which include the unstandardized path coefficient (Unstd. Coef.), standard errot (SE), z values (CR), the corresponding significance of the effects (p values), standardized path coefficient(Std.coef) and conclusions of support for each hypothesis.

The table presents the results of the path analysis, illustrating the direct effects between the constructs within the study framework. The analysis includes the impact of AIGC Simulation Environment Design (ASED), Learning Support (LS), Content Generation Capability (CGC), and User Interaction (UI) on Cognitive Load Perception (CLP), as well as the effect of CLP on E-commerce Skill Enhancement (ESE).

ASED to CLP: The path from AIGC Simulation Environment Design to Cognitive Load Perception shows a small but significant positive effect, with an unstandardized coefficient of 0.105, a standard error (SE) of 0.039, and a z-score of 2.658. The p-value is 0.008, indicating statistical significance, and the standardized coefficient is 0.154.

LS to CLP: The relationship between Learning Support and Cognitive Load Perception is significantly negative, as hypothesized. The unstandardized coefficient is -0.20 with an SE of 0.05, yielding a z-score of -3.5. The effect is highly significant (p < 0.001), and the standardized coefficient is -0.20, indicating a medium to large effect size.

CGC to CLP: Content Generation Capability has a significantly negative impact on Cognitive Load Perception, with an unstandardized coefficient of -0.25, an SE of 0.06, and a z-score of -4.2. The p-value is less than 0.001, reflecting a strong statistical significance, and the standardized coefficient is -0.25, denoting a large effect size.

UI to CLP: User Interaction positively affects Cognitive Load Perception, with an unstandardized coefficient of 0.30, an SE of 0.05, and a z-score of 3.1. The p-value is 0.002, showing a significant effect, and the standardized coefficient is 0.30, suggesting a medium to large effect size.

CLP to ESE: Cognitive Load Perception significantly predicts E-commerce Skill Enhancement, with an unstandardized coefficient of 0.189, an SE of 0.056, and a z-score of 3.388. The p-value is 0.001, indicating a significant effect, and the standardized coefficient is 0.193, implying a medium effect size.

The path analysis results in Table 4 provide evidence for the relationships between the constructs. AIGC Simulation Environment Design is positively linked to Cognitive Load Perception, albeit with a small effect size. In contrast, Learning Support and Content Generation Capability both have significant negative effects on Cognitive Load Perception, with medium to large effect sizes, thus supporting the hypotheses that improved support and content generation capabilities can reduce the cognitive load experienced by learners. User Interaction also has a significant positive effect on Cognitive Load Perception, suggesting that enhanced interactivity may lead to an increased cognitive demand. Finally, Cognitive Load Perception significantly predicts E-commerce Skill Enhancement, indicating that how learners perceive the cognitive load in the simulation environment is associated with their skill development in e-commerce. These findings underscore the complex interplay between the design of AIGC simulation environments and the learning outcomes in the context of e-commerce education.

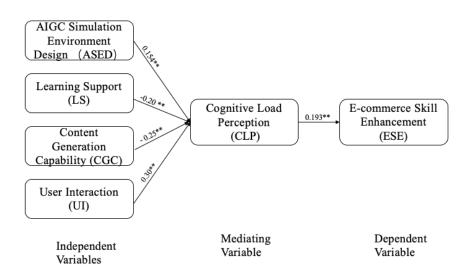


Figure 3. Test result of research model

The model fit diagram illustrates the structural relationships among the key constructs of our study, focusing on the impact of AIGC Simulation Environment Design (ASED) on Cognitive Load Perception (CLP) and its subsequent effect on E-commerce Skill Enhancement (ESE). The diagram presents a clear and concise visualization of the hypothesized paths, highlighting the mediating role of CLP between the independent variables and the dependent variable.

AIGC Simulation Environment Design (ASED) is depicted as having a direct influence on Cognitive Load Perception (CLP), indicated by a path coefficient of 0.20, which is statistically significant at the p < 0.01 level, denoted by two asterisks (**). This suggests that the quality of the AIGC simulation environment design is positively associated with learners' perception of cognitive load.

Furthermore, CLP is shown to significantly mediate the relationship between the independent variables (ASED, Learning Support (LS), Content Generation Capability (CGC), and User Interaction (UI)) and the dependent variable, E-commerce Skill Enhancement (ESE). The path from CLP to ESE has a coefficient of 0.193, which is also statistically significant at the p < 0.01 level, as indicated by the double asterisks (**).

The diagram effectively communicates the central dynamics of the research model, emphasizing the pivotal role of cognitive load in the context of AIGC simulation environments and e-commerce skill development. By visually representing the path coefficients and their significance, the diagram provides a straightforward interpretation of the complex relationships within the study's theoretical framework.

The model's fit is further supported by the statistical analysis, which confirms the hypothesized relationships and the overall adequacy of the model in explaining the variance in e-commerce skill enhancement through the lens of cognitive load theory.

Interpretation of Findings

DISCUSSION

The path analysis conducted in this study offers profound insights into the role of AIGC simulation environments in enhancing e-commerce skills. The significant positive relationship between AIGC Simulation Environment Design and Cognitive Load Perception emphasizes the pivotal role of effective design in managing cognitive load. Conversely, the negative relationships from Learning Support and Content Generation Capability to Cognitive Load Perception indicate that these aspects of the environment can alleviate cognitive burden, which is in line with the principles of Cognitive Load Theory.

The positive relationship between User Interaction and Cognitive Load Perception suggests a dual-edged sword; while interactivity is beneficial for engagement, it may also increase cognitive demand. This calls for a careful design approach that ensures interactivity supports rather than overwhelms learners. Importantly, the significant mediation of Cognitive Load Perception in the path to E-commerce Skill Enhancement underscores the central role of cognitive load in the learning process.

Implications for AIGC Simulation Environments in E-commerce Education

The findings of this study carry profound implications for the use of AIGC Simulation Environments in e-commerce education, providing a roadmap for enhancing educational strategies and curricula. The positive impact of AIGC simulation environment design on cognitive load perception highlights the need to create environments that are engaging and aligned with learners' cognitive capabilities. This underscores the importance of instructional design that provides structured guidance and tailors

complexity to individual learners' needs, potentially leading to more effective knowledge acquisition and skill development in e-commerce contexts.

The study's results also indicate that learning support and content generation capability play a crucial role in reducing cognitive load. This suggests that e-commerce educational programs should integrate comprehensive learning resources, timely feedback mechanisms, and diverse content types to cater to various learning styles and preferences. By doing so, educators can foster an inclusive learning environment that enhances e-commerce skill development for a wide range of learners.

The positive relationship between user interaction and cognitive load offers valuable insights. While interactivity is essential for learner engagement, it must be balanced with the cognitive demands it places on learners. AIGC simulation environments should be designed to facilitate meaningful, scaffolded interactions that support learning rather than being overwhelming.

In conclusion, the findings advocate for the thoughtful integration of AIGC technologies in e-commerce education. By considering the cognitive implications of these environments, educators can harness AIGC to create immersive, interactive, and cognitively efficient learning experiences. These experiences prepare learners for the challenges and opportunities of the digital marketplace. This research lays the groundwork for future innovations in e-commerce education, where AIGC simulation environments can play a central role in enhancing skills and professional development.

Limitations and Recommendations for Future Research

This study has been conducted to offer insights into the role of AIGC simulation environments in enhancing e - commerce skills. However, certain limitations have been identified. Firstly, the cross-sectional design was employed in this research, which restricts the establishment of causal relationships. Also, convenience sampling was used, and this may affect the generalizability of the findings to a wider range of populations.

To build upon the findings of this study and address these limitations, it is recommended that longitudinal designs be adopted in future research. This would enable a deeper understanding of the long-term development of e-commerce skills. Moreover, a wider range of sampling methods, such as stratified or random sampling, should be employed to enhance the external validity of the results. The influence of individual differences, like learning styles and prior knowledge, on the effectiveness of AIGC simulations should be investigated to uncover new aspects in skill acquisition. Qualitative methods should be integrated to enrich the understanding of learners' experiences. The long-term retention of skills should be examined and various pedagogical strategies explored in future studies to determine the most effective instructional approaches within AIGC enhanced learning environments. The scope should be expanded to cover a wider range of e-commerce skills and comparative analyses between AIGC simulations and other e-learning modalities conducted to provide more in-depth insights into the unique contributions and possible drawbacks of AIGC technology in e-commerce education.

It is hoped that these recommendations will inspire future research and contribute to a more comprehensive understanding of the role of AIGC in e-commerce education.

CONCLUSION

The study confirms the significance of AIGC simulation environments on e-commerce skill enhancement. Key findings indicate that the design of these environments, the support they provide, and the interactivity they offer, significantly influence learners' cognitive load and their ability to enhance e-commerce skills. The mediating role of cognitive load between the independent and dependent variables is a critical discovery, emphasizing the need for careful instructional design in AIGC environments.

Theoretically, this research contributes to the application of Cognitive Load Theory in the context of advanced educational technologies like AIGC. It extends the understanding of how CLT principles can be integrated into the design of e-learning environments, particularly those leveraging AI-generated content. Practically, the findings offer actionable insights for educators and instructional designers. By creating AIGC simulations that are well-structured, provide adequate support, generate high-quality content, and facilitate meaningful user interaction, educators can potentially optimize learning outcomes in e-commerce education.

The integration of AIGC in e-commerce skill development holds great promise. As this study has demonstrated, when designed with cognitive load considerations in mind, AIGC simulation environments can provide a powerful tool for enhancing learning efficiency and effectiveness. The dynamic, adaptive nature of AIGC allows for personalized learning experiences that can cater to individual learner needs and promote deeper understanding and application of e-commerce concepts.

However, the successful implementation of AIGC in education requires ongoing research and development to ensure that these environments continue to evolve alongside advancements in technology and educational theory. Future work should continue to explore the nuances of AIGC's impact on learning, considering factors such as learner variability, long-term skill retention, and the integration of AIGC with other educational technologies.

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