# A Survey of Self-Regulated Learning, Generative AI Literacy, E-Commerce, Technology Acceptance, Instructional Design, Higher Education, and Digital Literacy




## Abstract

This survey paper explores the interdisciplinary nexus of self-regulated learning, generative AI literacy, e-commerce, technology acceptance, instructional design, higher education, and digital literacy. It addresses the pressing need for AI literacy in tertiary education, emphasizing the integration of digital technologies to enhance self-regulated learning (SRL) and the role of AI in educational experiences. Utilizing qualitative methodologies, the survey investigates the complexities of SRL, the integration of AI literacy into curricula, and the factors influencing technology acceptance in e-commerce. It also examines instructional design principles to foster digital literacy and analyzes higher education's role in developing digital competencies. The survey highlights the emergence of 'prompt literacy' for effective AI interaction and assesses societal attitudes toward AI. It underscores the importance of adaptive technologies in SRL, the ethical considerations of AI in e-commerce, and the challenges of integrating AI literacy into education. The paper concludes by suggesting future research directions, including the development of structured AI literacy programs, refining SRL data collection, and enhancing learning analytics systems. This comprehensive framework aims to address the challenges and opportunities at the intersection of these critical areas, providing insights for academic and professional settings.


## 1 Introduction

### 1.1 Interdisciplinary Exploration

This survey undertakes an interdisciplinary exploration that synthesizes fields such as self-regulated learning, generative AI literacy, e-commerce, technology acceptance, instructional design, higher education, and digital literacy. This multifaceted approach addresses the urgent need for AI literacy skills in higher education, advocating for comprehensive educational strategies [1]. The integration of digital technologies is essential for fostering self-regulated learning, enabling university students to manage their learning autonomously and bridging gaps in understanding technology's role in self-regulated learning strategies [2]. Additionally, the survey investigates the cutting-edge applications of Large Language Models (LLMs) in persuasion, assessing their influence on attitudes and behaviors across various domains, including politics, marketing, and public health [3].

Qualitative methodologies enhance the understanding of self-regulated learning by examining the complexities and contextual factors influencing these processes [4]. This is complemented by an analysis of students' perceptions of AI applications that support self-regulated learning in online environments, emphasizing AI's role in enriching educational experiences [5]. The survey also identifies factors contributing to the success of online educational courses, particularly in graduate

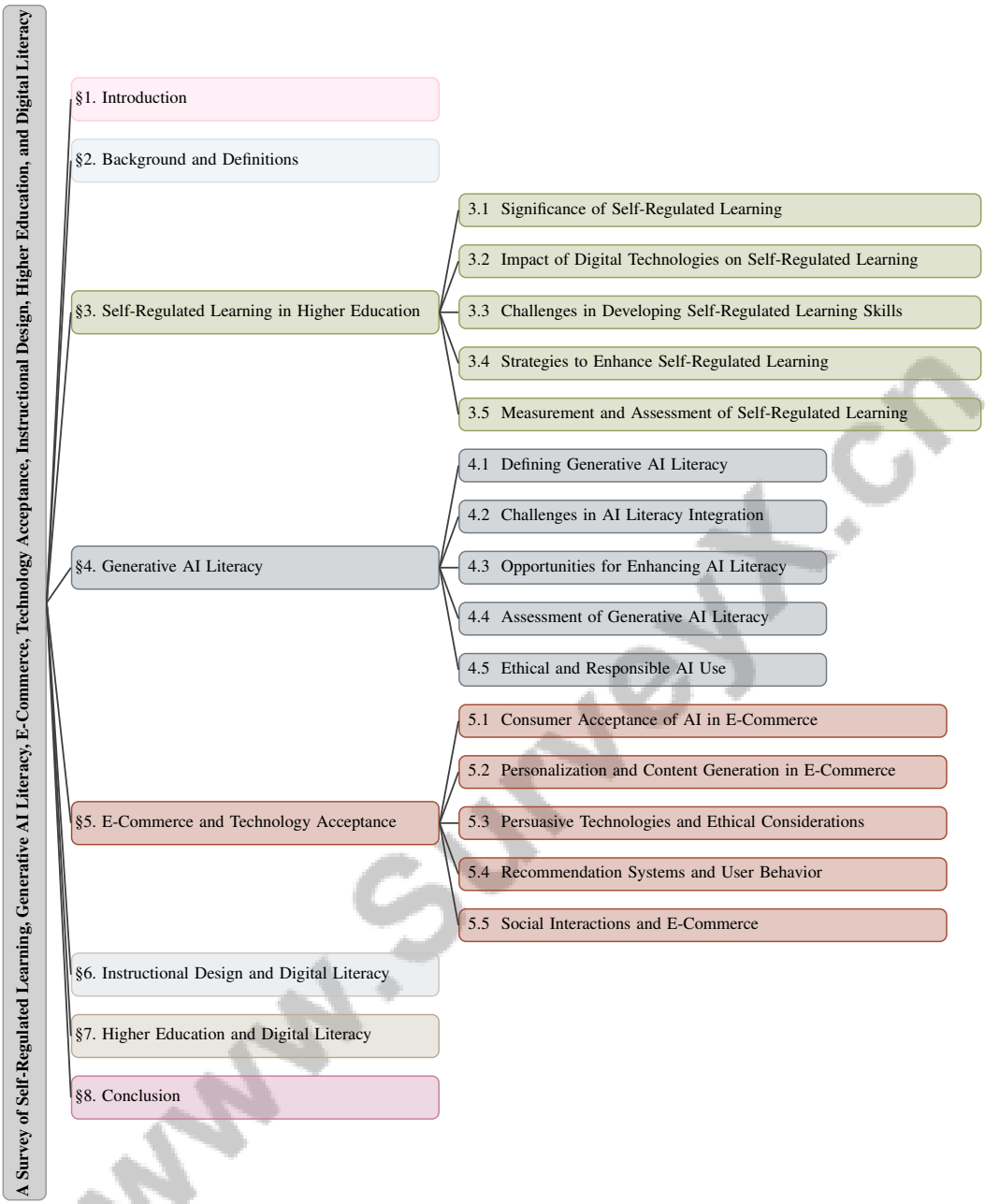


Figure 1: chapter structure

computer science programs, which are vital for comprehending student cognition and learning outcomes [6].

In language learning, the survey explores strategies that promote self-regulation and collaboration skills, which are crucial for acquiring a second or foreign language in varied learning contexts [7]. It highlights the underrepresented perspectives of students regarding AI use in higher education, stressing the need for improved AI literacy among students and educators [8]. The emerging concept of 'prompt literacy' is also discussed, which is essential for effective engagement with generative AI systems [9]. Finally, societal attitudes towards AI and AI literacy are assessed, addressing the broader implications of AI on society and individual well-being [10]. This interdisciplinary survey offers a robust framework for understanding and addressing the challenges and opportunities at the intersection of these critical areas.



AI-generated, for reference only.

### 1.2 Structure of the Survey

The survey is systematically organized into interconnected sections, each addressing a vital aspect of the interdisciplinary exploration. It begins with an introduction that outlines the significance of self-regulated learning, generative AI literacy, e-commerce, technology acceptance, instructional design, higher education, and digital literacy, laying the groundwork for subsequent discussions.

The second section, "Background and Definitions," provides a thorough overview of core concepts, defining key terms and elucidating their interconnections and relevance, which is essential for grasping the complex dynamics explored in later sections.

Next, the survey examines "Self-Regulated Learning in Higher Education," focusing on its role in academic success and lifelong learning. This section addresses the impact of digital technologies on self-regulated learning processes, the challenges faced by students, strategies for skill enhancement, and methods for measurement and assessment.

The "Generative AI Literacy" section follows, investigating the integration of AI literacy into educational curricula, defining its components, and exploring associated challenges, opportunities, and ethical considerations. This section draws on recent experimental studies regarding the persuasive capabilities of LLM systems [3].

Subsequently, the survey analyzes "E-Commerce and Technology Acceptance," focusing on factors influencing consumer acceptance of AI in e-commerce, including personalization, ethical considerations, recommendation systems, and social interactions.

The forthcoming section on "Instructional Design and Digital Literacy" will explore instructional design principles aimed at enhancing digital literacy among students and faculty. It will cover technology integration in educational frameworks, the importance of constructive feedback, and the incorporation of reflective practices. The emerging significance of AI literacy, particularly in utilizing generative tools like ChatGPT to foster critical thinking and ethical technology use, will also be highlighted. The role of librarians in facilitating digital and information literacy will be emphasized, showcasing their contribution to developing essential research skills and promoting responsible AI tool usage in higher education [11, 12].

The penultimate section, "Higher Education and Digital Literacy," will investigate the interplay between these domains, focusing on educator preparedness, the role of MOOCs, learning analytics, and strategies for late-career learners.

The survey concludes by synthesizing key findings related to the integration of human and analytics feedback in enhancing student engagement and performance in reflective writing tasks. It discusses implications for academic and professional settings and suggests future research directions to explore the sustainability and applicability of these feedback approaches across diverse educational contexts [13, 4]. This structured approach ensures a comprehensive exploration of the intricate interplay between these critical areas.The following sections are organized as shown in Figure 1.

## 2 Background and Definitions

### 2.1 Defining Core Concepts

Self-regulated learning (SRL) involves learners actively managing their education through cognitive, metacognitive, motivational, and behavioral strategies. Essential elements include goal setting, self-monitoring, and self-reflection, crucial for academic success and lifelong learning, especially in digitally enhanced higher education environments. Personalized learning experiences allow learners to tailor strategies to their needs, enhancing SRL's effectiveness, particularly when integrated with collaborative and mobile-assisted language learning (MALL) [14, 7].

Generative AI literacy, a critical competency for researchers and practitioners, involves understanding, critiquing, and ethically using AI technologies [15]. This literacy includes fluency in generative and conventional AI, awareness of their capabilities, potential misinformation, and ethical issues, particularly with Large Language Models (LLMs) [3]. 'Prompt literacy,' a key aspect, involves crafting precise prompts for AI systems, interpreting outputs, and iteratively refining these prompts [9].

E-commerce, defined by online transactions, benefits significantly from AI technologies that enhance personalization and consumer experiences. Understanding technology acceptance is vital for consumer adaptation, affecting e-commerce platform success. Challenges like unreliable AI outputs highlight the importance of technology acceptance in these environments [16].

Instructional design is a systematic approach to creating educational experiences that enhance learning and performance. It is crucial for developing digital literacy, encompassing skills necessary for effective digital technology navigation across various contexts [17]. In higher education, integrating AI technologies requires fostering AI literacy among students and educators to ensure effective usage [8].

Higher education institutions, including universities and colleges, significantly promote digital, data, and AI literacy, preparing students for a digitized world. Digital literacy enables critical engagement with digital content and tools, fostering responsible digital age participation [18]. Developing nuanced measures to assess attitudes and literacy regarding AI across diverse populations further underscores the importance of these competencies [10].

### 2.2 Interconnections and Relevance

The interdisciplinary examination of SRL, generative AI literacy, e-commerce, technology acceptance, instructional design, higher education, and digital literacy reveals their intricate interconnections and significance in contemporary educational and professional landscapes. Central to this exploration is integrating adaptive technologies with SRL, highlighting personalized learning environments' role in enhancing SRL capabilities [14]. Such environments empower learners to customize their educational experiences, fostering autonomy and engagement.

The survey presents a nuanced perspective emphasizing cultural and contextual factors in shaping AI attitudes, highlighting the need for AI literacy programs sensitive to these dynamics [10]. This approach is particularly pertinent in higher education, where developing digital and AI literacy among educators is essential for navigating and imparting knowledge in a rapidly digitizing world.

The interconnections between SRL and technology acceptance are evident in how learners leverage digital tools to support their learning processes. Integrating SRL strategies with technology enhances learning experiences and addresses cognitive, motivational, and emotional learning aspects, as conceptualized in various models [19]. The survey categorizes these strategies into information sharing, active presence, documentation, classification, and collaborative learning, integral to effective technology use [18].

In e-commerce, LLMs play a significant role in persuasive communication, generating human-like content that influences consumer attitudes and behaviors. This capability enhances technology acceptance and consumer experience, particularly through systematically evaluating structured data for product data mining [20]. Developing prompt literacy is essential for students to engage effectively with AI systems, refining their learning strategies [9].

Finally, addressing older workers' hesitancy to engage with new technologies is critical for leveraging their extensive experience in digital contexts, ensuring they remain active participants in the evolving technological landscape [21]. These interconnections underscore the survey's significance, providing a comprehensive framework for understanding and addressing challenges and opportunities at these critical areas' intersection.

## 3 Self-Regulated Learning in Higher Education

In higher education, self-regulated learning (SRL) is crucial for students to autonomously and effectively navigate their academic paths. This section explores SRL's significance, focusing on its role in fostering academic success and lifelong learning, particularly in self-directed learning environments. Figure 2 illustrates the hierarchical structure of Self-Regulated Learning (SRL) in this context, highlighting its significance alongside the impact of digital technologies, challenges, enhancement strategies, and assessment methods. The diagram categorizes the main concepts and subcategories, emphasizing the relationships and importance of each element in fostering SRL among students. By visualizing these connections, we can better understand how SRL can be effectively cultivated within educational frameworks. Additionally, Table 5 presents a detailed categorization of



AI-generated, for reference only.

| Category | Feature | Method |
|---|---|---|
| **Significance of Self-Regulated Learning** | Predictive and Process Analysis<br>Feedback and Analytics | FM-RF[22]<br>TCB[23] |
| **Impact of Digital Technologies on Self-Regulated Learning** | Adaptive Learning Technologies | KTM[24], PARB[25] |
| **Challenges in Developing Self-Regulated Learning Skills** | Personalized Learning Support | PSHA[26] |
| **Strategies to Enhance Self-Regulated Learning** | AI-Enhanced Frameworks<br>Observational and Analytical Methods<br>Data-Driven Insights<br>Personalization and Customization | LASPM[27]<br>RR[28]<br>IM[29], FE[30]<br>PBFI[13] |
| **Measurement and Assessment of Self-Regulated Learning** | Feedback Systems | ROLE[14] |

Table 1: This table provides a comprehensive overview of various methodologies employed in the study of self-regulated learning (SRL) within higher education contexts. It categorizes the methodologies based on their focus areas, including the significance of SRL, the impact of digital technologies, challenges in skill development, enhancement strategies, and measurement and assessment techniques. Each category is further detailed with specific features and methods, highlighting the diverse approaches and tools used to support and analyze SRL processes.

methods and strategies pertinent to the study and enhancement of self-regulated learning (SRL) in higher education, illustrating the integration of digital technologies and personalized learning support mechanisms.

### 3.1 Significance of Self-Regulated Learning

| Method Name | Learning Environments | Cognitive Processes | Educational Outcomes |
|---|---|---|---|
| KTM[24] | Online Learning Environment | Cognitive Metacognitive Strategies | Improving Learning Outcomes |
| FM-RF[22] | Higher Education | Cognitive, Metacognitive, Motivational | Academic Performance |
| PBFI[13] | Online Settings | Cognitive Processes | Academic Performance |
| TCB[23] | Learning Management System | Metacognitive Motivational Processes | Enhance Student Engagement |
| IM[29] | E-learning Environments | Self-regulation Strategies | Educational Outcomes |
| ROLE[14] | Formal And Informal | Meta-cognitive Skills | Knowledge Retention |

Table 2: Overview of various methods and their application in different learning environments, highlighting the cognitive processes involved and the educational outcomes achieved. This table provides a comparative analysis of strategies aimed at enhancing self-regulated learning across diverse educational contexts.

Self-regulated learning (SRL) is essential in higher education, where students encounter complex, self-directed learning scenarios. It involves cognitive, metacognitive, and motivational processes that empower learners to pursue their educational goals [19]. SRL's importance is heightened in online and flexible learning environments, where it significantly impacts academic performance [18]. Digital tools further underscore SRL's critical role by enhancing learning experiences and outcomes [17]. Effective SRL strategies can markedly improve academic achievement across diverse educational contexts [31]. Developing cognitive and metacognitive strategies provides insights into learners' thought processes, facilitating a deeper understanding of SRL [24]. Table 2 presents a comprehensive comparison of methods employed to facilitate self-regulated learning, detailing their respective learning environments, cognitive processes, and educational outcomes.

Engaging students in designing learning analytics (LA) indicators is vital for their acceptance and usability, reinforcing SRL's significance in academic success [32]. This involvement fosters connections with learning materials and cultivates self-regulation skills. Predictive models using historical transcript data can forecast student performance, enabling targeted interventions to enhance SRL [22]. The challenge of developing self-regulation and collaboration skills among language learners in mobile environments further illustrates SRL's importance in diverse educational settings [7]. Additionally, reflective writing, which requires high self-regulation, poses significant challenges for students, underscoring the need for robust SRL skills [13].

In higher education, insufficient support for self-study activities often leads to low engagement and poor outcomes, highlighting the necessity for enhanced SRL strategies [23]. Effective instructional design, guided by process mining studies, can model and enhance students' SRL processes, improving academic achievement [29]. Promoting SRL in secondary education is also vital for preparing students for higher education challenges [33]. Ultimately, SRL is indispensable for academic success and lifelong learning, necessitating its integration into educational curricula and support systems to equip students with the competencies required to excel in modern learning environments [14].

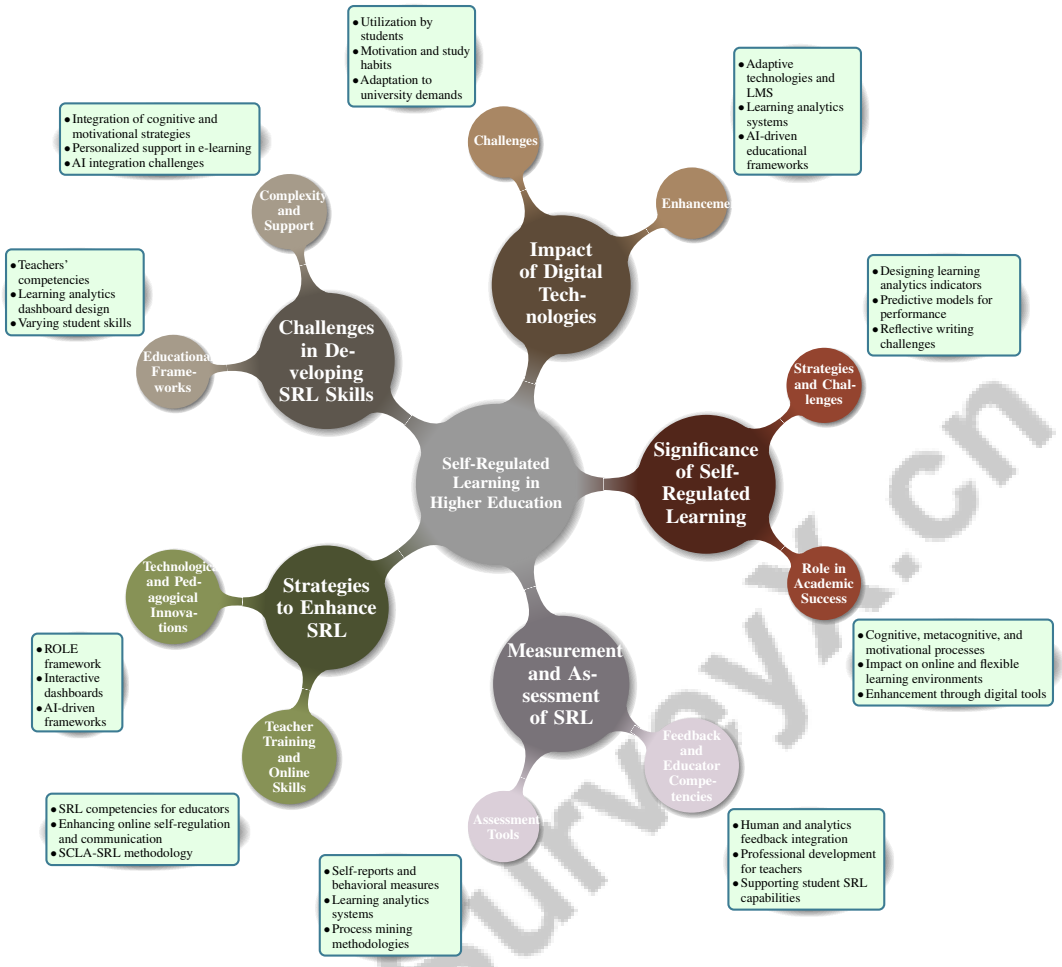


Figure 2: This figure illustrates the hierarchical structure of Self-Regulated Learning (SRL) in higher education, highlighting its significance, the impact of digital technologies, challenges, enhancement strategies, and assessment methods. The diagram categorizes the main concepts and subcategories, emphasizing the relationships and importance of each element in fostering SRL among students.

### 3.2 Impact of Digital Technologies on Self-Regulated Learning

| Method Name | Technological Tools | Support Mechanisms | Implementation Challenges |
|---|---|---|---|
| ROLE[14] | Adaptive Technologies | Adaptive Support Systems | Lack OF Motivation |
| KTM[24] | Learning Logs | Personalized Feedback | Lack Motivation |
| PSHA[26] | Mobile App | Personalized Feedback | Lack OF Motivation |
| PARB[25] | Adaptive Systems | Adaptive Feedback | Inadequate Srl Skills |
| RR[28] | - | Personalized Feedback | Inadequate Srl Skills |

Table 3: This table presents an overview of various methods employing digital technologies to support self-regulated learning (SRL). It details the technological tools utilized, support mechanisms provided, and the implementation challenges faced, highlighting the critical role of adaptive technologies and personalized feedback in enhancing SRL.

Digital technologies significantly enhance self-regulated learning (SRL) by providing tools and platforms that improve cognitive and metacognitive skills. Technologies like hypermedia and mobile devices create dynamic learning environments that require active engagement in SRL strategies [32]. Adaptive technologies, including Learning Management Systems (LMS), support SRL by offering personalized feedback and facilitating learner autonomy, though traditional LMS often lack the individualized support essential for effective SRL [14]. Learning analytics (LA) systems enhance

feedback processes and support SRL through continuous data collection and iterative feedback loops, allowing the modeling of cognitive and metacognitive strategies [24].

As illustrated in Figure 3, the impact of digital technologies on SRL encompasses not only the benefits of these tools but also the challenges associated with their utilization. The figure highlights key technological tools, such as hypermedia and mobile devices, and emphasizes the role of adaptive support systems in enhancing SRL. It further addresses the challenges students face, including motivation issues and a lack of SRL skills, underscoring the significance of adaptive support through writing support systems, feedback loops, and learning analytics in fostering effective SRL. Additionally, Table 3 provides a comprehensive analysis of different methods leveraging digital technologies to enhance self-regulated learning, detailing the tools, support systems, and challenges associated with their implementation.

Despite the potential of digital technologies to enhance SRL, many students struggle to utilize these tools effectively. This challenge is often exacerbated by a lack of motivation or ability to implement beneficial study habits, as illustrated by the Fogg Behavioral Model [26]. Furthermore, many secondary school students enter higher education without the necessary SRL skills, complicating their adaptation to university demands [33]. Adaptive writing support systems have shown to influence students' revision behavior and SRL, indicating the potential of digital technologies to bolster learning processes [25]. However, previous research's reliance on generalized self-reports and experimental designs limits the nuanced understanding of SRL in natural classroom contexts [28]. Addressing these challenges requires ongoing support to help students effectively harness digital technologies for autonomous learning.

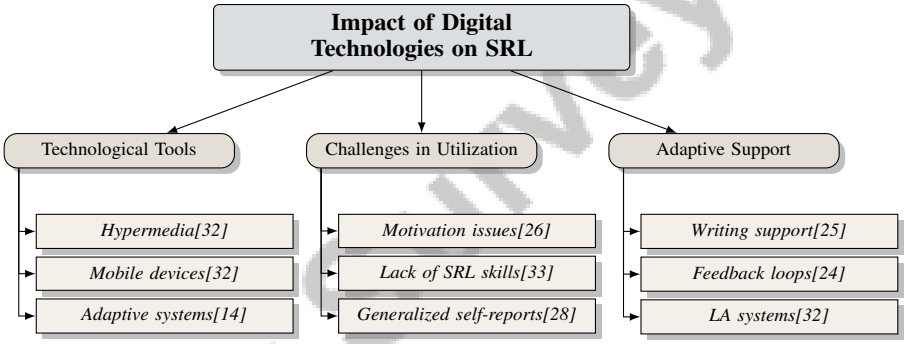


Figure 3: This figure illustrates the impact of digital technologies on self-regulated learning (SRL), highlighting key technological tools, challenges in their utilization, and the role of adaptive support systems. It emphasizes the importance of technologies like hypermedia, mobile devices, and adaptive systems in enhancing SRL, while also addressing challenges such as motivation issues and lack of SRL skills. Additionally, it underscores the significance of adaptive support through writing support systems, feedback loops, and learning analytics (LA) systems in fostering effective SRL.

### 3.3 Challenges in Developing Self-Regulated Learning Skills

Developing self-regulated learning (SRL) skills presents several challenges, particularly in higher education, where students navigate complex learning environments with varying support levels. A primary challenge is the complexity of SRL processes, which require integrating cognitive, metacognitive, and motivational strategies for effective learning management [5]. This complexity is heightened by the need for personalized support, as students often lack tailored guidance in e-learning environments [29]. Integrating AI applications into existing learning frameworks poses additional challenges, as these technologies must support SRL without overwhelming students or disrupting established learning processes [5]. Additionally, the impact of technology on self-regulation outcomes is complex, requiring a nuanced understanding of the direct and indirect effects of technological interventions on SRL [17].

Another significant challenge is the inadequacy of current educational frameworks in addressing the interplay between teachers' competencies as self-regulated learners and their roles in facilitating SRL [34]. This gap often leaves students without the scaffolding needed to develop robust SRL skills, particularly in online settings where direct support is limited [29]. The design of learning analytics

(LA) dashboards illustrates challenges in supporting SRL, as a disconnect often exists between tool designers and learners, resulting in indicators that may not meet learners' needs [32]. Additionally, the varying self-regulation and communication skills of students in online environments present challenges for instructors, who may not have sufficient preparation time to adapt their teaching methods [18].

Conflicting results from studies on the effectiveness of SRL strategies highlight the need for comprehensive analyses to identify the most beneficial strategies and their conditions [31]. The success of SRL interventions relies heavily on student engagement and their willingness to adopt new habits, which can vary significantly among individuals [26]. To effectively address the challenges of fostering SRL in educational settings, a comprehensive strategy is essential, incorporating personalized support systems, seamless integration of AI technologies, and ongoing refinement of educational frameworks. This multifaceted approach aims to enhance the capabilities of both educators and learners, facilitating the development of robust SRL skills crucial for academic success and lifelong learning in an increasingly digital world. Recent research underscores the importance of considering diverse learners' unique needs and the evolving demands of contemporary education [25, 35, 34, 14, 5].

### 3.4 Strategies to Enhance Self-Regulated Learning

Enhancing self-regulated learning (SRL) among students requires an integrative approach that combines technological advancements, pedagogical innovations, and personalized feedback mechanisms. The Responsive Open Learning Environments (ROLE) framework exemplifies this approach, allowing learners to customize their learning environments while receiving appropriate SRL support [14]. This customization empowers learners to tailor their educational experiences to their needs, fostering engagement and autonomy. Interactive dashboards, such as FlippED, are crucial for visualizing students' SRL profiles and behaviors, providing educators with insights necessary for targeted interventions [30]. These tools, coupled with fine-grained observational methods like running records and retrospective interviews, enable educators to capture SRL dynamics within classroom settings, informing context-specific intervention design [28].

AI-driven educational frameworks offer structured support for various SRL phases—forethought, performance, and reflection—across cognitive, metacognitive, and behavioral dimensions [5]. By providing personalized feedback and adaptive learning environments, these AI applications cater to individual learning needs, enhancing SRL practices. Moreover, technology-enhanced environments incorporating specific monitoring strategies significantly improve SRL outcomes by equipping students with tools and feedback for self-monitoring and adjusting their learning processes [17]. The integration of analytics feedback with human feedback has been shown to enhance students' engagement and performance in reflective writing tasks, illustrating the potential of combining data-driven insights with personalized guidance to support SRL [13]. Process mining of event logs from Learning Management Systems (LMS), using algorithms like the Inductive Miner, provides a method to assess and enhance SRL by interpreting models that reveal students' learning behaviors [29]. This analytical approach supports identifying effective learning pathways and interventions that promote self-regulation.

Teacher training programs focusing on SRL competencies are essential for equipping educators with the skills needed to foster self-regulation among students [34]. These programs should emphasize comprehensive SRL skill development rather than isolated competencies, fostering independent learners [33]. Additionally, enhancing self-regulation and communication skills in online settings is crucial for adapting to the increasing prevalence of digital learning environments [18]. The Student-Centered Learning Analytics-enhanced Self-Regulated Learning (SCLA-SRL) methodology integrates SRL models with human-computer interaction (HCI) and information visualization (InfoVis) guidelines to enhance learning experiences [32]. This comprehensive framework supports the design of learning analytics systems aligned with students' expectations and performance, providing timely feedback that fosters self-regulation [27].

### 3.5 Measurement and Assessment of Self-Regulated Learning

The measurement and assessment of self-regulated learning (SRL) in educational settings require a comprehensive approach encompassing cognitive, metacognitive, and behavioral dimensions. Effective assessment tools are vital for enhancing SRL and improving academic outcomes. Self-

| Benchmark | Size | Domain | Task Format | Metric |
|---|---|---|---|---|
| GLAT[36] | 355 | Genai Literacy | Multiple Choice Questions | Cronbach's alpha; omega total |
| LLM-ECom[37] | 1,856,000 | Product Classification | Classification | F1 score, Rouge-L |
| EcomInstruct[38] | 2,500,000 | E-commerce | Instruction Tuning | ROUGE-L, F1 |
| WebArena[39] | 812 | E-commerce | Task Completion | Functional Correctness |
| NLQ-ECom[40] | 3,540 | Product Search | Natural Language Query | Inter-annotator agreement, Key facts accuracy |
| HILB[41] | 117 | Education | Writing Task | Essay Score Improvement, Intrinsic Motivation |
| KGC-LLM[42] | 1,445 | E-commerce | Relation Labeling | Accuracy, Precision |
| PLP-Benchmark[43] | 15,859 | E-commerce | Product Placement Auditing | Percentage of PL Products in Ads, Click-Through Rate |

Table 4: This table provides an overview of various benchmarks relevant to the assessment of self-regulated learning and related domains. It details the benchmark names, their respective sizes, domains of application, task formats, and the metrics used for evaluation. Such comprehensive benchmarking is crucial for the development and validation of effective educational tools and methodologies.

reports remain a common method for assessing students' self-regulation levels, offering insights into their perceptions and strategies. However, these self-reports should be complemented by objective behavioral measures to ensure precise calibration of specific SRL strategies [14]. Learning analytics (LA) systems are increasingly employed in educational contexts to monitor SRL processes. These systems utilize ambient trace data to provide timely predictions and feedback, empowering students to adjust their learning strategies effectively. For instance, tools that incorporate chat-based interactions can deliver writing tasks and feedback, enhancing the self-study experience by providing individualized feedback to large cohorts, improving accessibility and mentoring efficiency [14].

Advanced methodologies such as process mining offer significant insights into SRL by analyzing students' interactions within learning management systems (LMS). By examining event traces from platforms like Moodle, process mining reveals patterns in students' SRL activities, supporting the identification of effective learning pathways and interventions that promote self-regulation. This analytical approach is crucial for understanding the nuances of SRL in naturalistic educational settings [14]. Feedback is pivotal in assessing SRL. Integrating human and analytics feedback has been shown to enhance students' engagement and performance, particularly in tasks requiring high self-regulation levels, such as reflective writing. This method exemplifies the potential of combining data-driven insights with personalized guidance to support SRL, leveraging models that emphasize motivation, ability, and habit formation [14].

Moreover, educators' competencies are integral to effective SRL instructional practices. Professional development programs focusing on enhancing teachers' SRL skills are essential, enabling educators to better support students in developing robust self-regulation capabilities. This relationship underscores the importance of equipping teachers with the necessary skills to foster SRL among learners [14]. Table 4 presents a detailed summary of representative benchmarks that are pertinent to the measurement and assessment of self-regulated learning, illustrating the diversity of domains, task formats, and evaluation metrics employed in current research.

| Feature | Significance of Self-Regulated Learning | Impact of Digital Technologies on Self-Regulated Learning | Challenges in Developing Self-Regulated Learning Skills |
|---|---|---|---|
| **Learning Environment** | Flexible Environments | Adaptive Technologies | E-learning Environments |
| **Cognitive Processes** | Metacognitive Strategies | Feedback Loops | Motivational Strategies |
| **Educational Outcomes** | Improved Performance | Enhanced Srl Skills | Variable Effectiveness |

Table 5: This table provides a comparative analysis of the significance, impact, and challenges associated with self-regulated learning (SRL) in higher education. It highlights how flexible learning environments, metacognitive strategies, and improved educational outcomes are influenced by digital technologies and the challenges faced in developing SRL skills. The table serves as a comprehensive overview of the methods and strategies pertinent to fostering SRL among students.

# 4 Generative AI Literacy

## 4.1 Defining Generative AI Literacy

Generative AI literacy entails a comprehensive understanding of artificial intelligence, focusing on critical engagement, ethical considerations, and innovative applications. It involves foundational AI knowledge and the capability to effectively interact with AI tools, solve problems, and promote ethical usage across various contexts [15]. The framework for AI literacy in education emphasizes personalized learning, assessment strategies, and ethical use, highlighting AI's transformative potential [8]. A key component, 'prompt literacy', requires generating precise prompts, interpreting AI outputs, and refining these prompts, particularly enhancing educational engagement and vocabulary learning [9]. Understanding societal attitudes towards AI is crucial for navigating its complexities, requiring a critical evaluation of its impact in educational and professional domains [10]. Integrating AI knowledge with information and digital literacy is essential, enabling learners to critically engage with digital content and technologies.

As illustrated in Figure 4, the key components of Generative AI Literacy—foundational knowledge, critical engagement, and innovative applications—are essential elements for understanding and utilizing AI effectively. This visual representation reinforces the importance of these components in fostering a holistic approach to AI literacy.

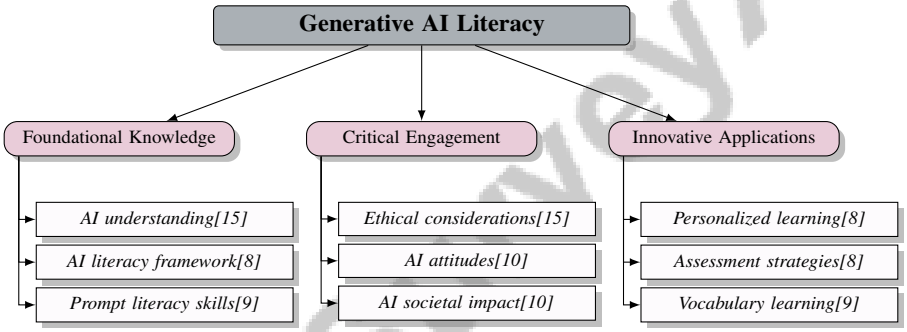


Figure 4: This figure illustrates the key components of Generative AI Literacy, highlighting foundational knowledge, critical engagement, and innovative applications as essential elements for understanding and utilizing AI effectively.

## 4.2 Challenges in AI Literacy Integration

Integrating AI literacy into education faces challenges, mainly due to the lack of a standardized definition and effective pedagogical approaches [1]. The absence of a clear framework complicates cohesive educational strategies for AI literacy. Existing LLM-empowered visualization systems often lack robustness in educational contexts [44]. Academic dishonesty risks, such as plagiarism and data hallucination, necessitate innovative assessment methods to maintain academic integrity [8, 15]. Privacy concerns and misinformation from AI tools present ethical challenges [11]. Metacognitive laziness, where learners overly rely on AI tools like ChatGPT, can reduce engagement and critical thinking, requiring strategies to foster active learning [41]. The underexploration of generative AI literacy levels affects engagement with chatbot technologies, while the lack of objective measures complicates AI literacy integration [45, 10].

## 4.3 Opportunities for Enhancing AI Literacy

Enhancing AI literacy involves strategically integrating it into educational curricula. Future research should develop pedagogical strategies that incorporate AI literacy, ensuring learners responsibly navigate and utilize AI technologies [1]. Embedding AI literacy into curricula bridges technological advancements and educational practices, enhancing competencies in digital and AI domains [11]. A framework categorizing chatbots into conventional (reactive) and scaffolding (proactive) types offers opportunities to tailor AI tools to diverse educational needs, enhancing learning experiences [45].

### 4.4 Assessment of Generative AI Literacy

Assessing generative AI literacy is vital for understanding learner engagement with AI technologies. A robust framework evaluates skills associated with AI literacy, including AI concepts, ethical considerations, and practical application skills. The Generative AI Literacy Test (GLAT) provides a foundational instrument with strong validity and reliability, predicting performance in AI-supported tasks [36]. Assessments evaluate proficiency in crafting precise prompts, interpreting outputs, and leveraging AI tools, essential for AI and prompt literacy [9, 11, 15, 8, 21]. Incorporating AI literacy assessments into curricula allows institutions to customize teaching strategies, fostering critical and ethical engagement with AI tools [11, 8, 9].

### 4.5 Ethical and Responsible AI Use

Ethical and responsible AI use is crucial in integrating AI literacy into education and professional practices. As AI systems become prevalent, fostering AI literacy is essential for advancing responsible research practices and critical engagement with these technologies [15]. Understanding ethical implications, such as privacy, data security, and algorithmic bias, is vital. Future research should develop comprehensive frameworks for responsible AI use, enhancing AI literacy across diverse populations [8]. The GLAT provides a reliable assessment of generative AI literacy, addressing self-reported measures' limitations and offering insights into ethical AI use [36]. Exploring emotional dynamics in AI interactions underscores the need for ethical guidelines in designing AI technologies [46]. Increasing dataset sizes and integrating advanced AI technologies are crucial for developing sophisticated and ethically sound AI systems.

## 5 E-Commerce and Technology Acceptance

### 5.1 Consumer Acceptance of AI in E-Commerce

Consumer acceptance of AI in e-commerce is shaped by trust, personalization, perceived usefulness, and ethical considerations. Trust is pivotal, as digital interactions replace face-to-face communication, making digital trust signals essential. The credibility of online reviews and ratings significantly influences consumer perceptions, with concerns about reviewer rationality and feedback authenticity [47]. Discrepancies between customer reviews and vendor descriptions can cause misunderstandings, negatively impacting satisfaction and acceptance [48].

As illustrated in Figure 5, the key factors influencing consumer acceptance of AI in e-commerce can be categorized into trust and reviews, personalization strategies, and social interactions and fraud. This figure highlights the importance of digital trust signals, review credibility, advanced personalization methods, and adaptive fraud control systems.

Personalization, driven by advanced AI applications, is crucial for acceptance, as it enables tailored content and recommendations that align with individual preferences. The AliMe MKG method, for instance, enhances acceptance by providing engaging, detailed product information [49]. However, inconsistencies in badge assignments can lead to confusion, highlighting the need for standardized personalization strategies [50].

Challenges such as the cold start problem, where models must adapt to new users and products, are prevalent in dynamic environments [51]. Personalized ad allocation on product detail pages, considering interactions with organic content, is vital for enhancing AI technology acceptance [52].

Social interactions within online networks significantly influence purchasing decisions, emphasizing the need for AI systems to incorporate social dynamics into recommendation algorithms [53]. The lack of effective methods to analyze conversational data on social media platforms remains a barrier to improving e-commerce services [54], and addressing this is crucial for boosting consumer engagement and acceptance of AI-driven platforms.

The evolving nature of fraud patterns in e-commerce necessitates adaptive fraud control systems. Traditional systems relying on static decision thresholds are inadequate, often failing to account for interactions among decision-making parties [55]. Implementing sophisticated, data-driven approaches can enhance trust and security, fostering greater consumer acceptance of AI technologies.

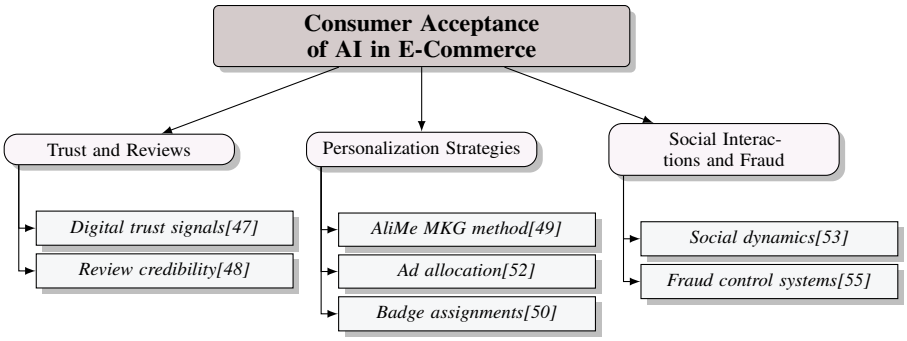


Figure 5: This figure illustrates the key factors influencing consumer acceptance of AI in e-commerce, categorized into trust and reviews, personalization strategies, and social interactions and fraud. It highlights the importance of digital trust signals, review credibility, advanced personalization methods, and adaptive fraud control systems.

### 5.2 Personalization and Content Generation in E-Commerce

AI significantly enhances personalization and content generation in e-commerce, tailoring consumer experiences to individual preferences and optimizing business outcomes. AI technologies facilitate customized shopping experiences, increasing consumer satisfaction and engagement. The AliMe MKG method, for example, integrates textual and visual information to enrich personalization and content generation, fostering a more interactive customer experience [49].

Knowledge graphs derived from catalog data refine attribute identification in e-commerce queries, enabling more precise personalization [56]. This is complemented by the Neural Rating Regression with Abstractive Tips Generation (NRT) model, which enhances recommendation systems by merging user-generated tips with numerical ratings, providing a richer context for personalization [57].

AI-driven content generation is further advanced by frameworks that blend advertising with organic content. The virtual bids approach optimizes ad placement by assessing the joint effects of ads and organic content, enhancing personalization and effectiveness in e-commerce platforms [52]. Additionally, a high-quality instruction dataset designed for e-commerce tasks supports the development of more effective AI models for content generation [51].

The dynamic nature of e-commerce necessitates systems that adapt to frequent product introductions and evolving consumer preferences. Lifelong learning embeddings address this challenge by dynamically extending input sizes while retaining learned knowledge, ensuring the efficacy of personalization strategies over time [58]. Furthermore, analyzing customer conversations through network text methodologies enables efficient identification of core topics related to customer experiences, facilitating targeted content generation [54].

The semantic gap between customer language in reviews and vendor language in product descriptions can lead to misunderstandings that affect consumer satisfaction and acceptance. An information-theoretical approach to measuring this gap can identify significant semantic drift, improving the alignment of product descriptions with consumer expectations [48]. Additionally, categorizing badges based on psychological triggers, such as Social Proof, Scarcity, and Exclusivity, provides a framework for understanding their influence on consumer behavior, enhancing personalization efforts [50].

### 5.3 Persuasive Technologies and Ethical Considerations

Persuasive technologies in e-commerce leverage advanced AI systems to influence consumer behavior, raising ethical considerations regarding transparency, accountability, and fairness. AI-driven personalization and content generation necessitate ethical frameworks that enhance consumer experiences without compromising ethical standards. A significant concern is the potential for misinformation and bias within AI models, which, while improving recommendation accuracy, can inadvertently perpetuate biases, affecting consumer trust and decision-making [59]. Utilizing comprehensive datasets from real-world e-commerce tasks is essential to mitigate these risks and ensure relevance [49].

The ethical implications of recommendation systems, particularly their explainability, are crucial for fostering user trust. Transparent systems that clarify their recommendations can enhance consumer confidence and facilitate informed purchasing decisions [60]. Moreover, adapting Social Network Analysis to model relationships between words provides a nuanced understanding of customer feedback, enabling businesses to address consumer concerns more effectively [46].

While social media enhances brand engagement and consumer trust, it also raises ethical concerns regarding privacy and data security. The deployment of persuasive technologies must balance consumer engagement with ethical standards to ensure sustainable practices [55]. Addressing the semantic gap between customer language in reviews and vendor language in product descriptions is crucial for improving alignment and enhancing consumer experiences [46].

Furthermore, ethical considerations extend to the benchmarks and datasets used in training AI models for e-commerce applications. Ensuring that benchmarks capture nuanced information needs expressed in natural language is vital to avoid inadequate training data [60]. This includes leveraging adaptive frameworks that generate relevant and concise questions reflecting critical aspects of reviews, thereby improving information retrieval for users [59].

### 5.4 Recommendation Systems and User Behavior

Recommendation systems are integral to e-commerce platforms, significantly influencing user behavior by providing personalized suggestions that enhance consumer engagement and satisfaction. These systems employ advanced AI methodologies to analyze extensive user data, predicting preferences and influencing purchasing decisions. The SEQ+MD framework exemplifies the application of multi-task sequence learning in recommendation systems, demonstrating superior performance over baseline models with datasets comprising over 20 million user-query-listing interaction sequences [16]. This framework highlights the importance of performance evaluation metrics such as AUC and nDCG in assessing the systems' impact on user behavior [59].

Semantic understanding techniques, such as BERT, integrated with nearest neighbor algorithms, enhance recommendation strategies by generating personalized suggestions based on user purchase behavior [49]. These approaches improve the relevance and accuracy of recommendations, thereby boosting user engagement. Metrics such as BLEU, ROUGE, precision, recall, and F1-scores across tasks like ad generation and product classification underscore the effectiveness of AI-driven recommendation systems in tailoring content to user preferences [16].

Moreover, integrating tripartite interaction information, as demonstrated in experiments on real-world datasets like LSEC-Small and LSEC-Large, provides insights into the systems' effectiveness in capturing user preferences and enhancing recommendation quality [61]. Optimizing compound recommendation models, such as JungleGPT, focuses on user interaction times and cost analysis, measuring inference costs and response times across various e-commerce tasks [62].

Cultural and regulatory aspects of user adoption of recommendation systems are crucial yet often overlooked, leading to incomplete insights into user behavior [63]. Addressing these factors is essential for developing comprehensive recommendation strategies that resonate with diverse user bases. Classifying online reviews as helpful or unhelpful using deep learning architectures like RCNN and pre-trained models such as BERT emphasizes the importance of user-generated content in shaping consumer trust and decision-making [54].

Furthermore, the ECC framework's performance evaluations on e-commerce conversation datasets from platforms like Taobao and Jing Dong illustrate the impact of user input matching and output similarity on recommendation effectiveness [53]. The method described by [48] optimizes ad allocation by modeling user click behavior, further influencing user behavior in e-commerce through improved ad performance metrics.

Experiments conducted with sales data from a major e-commerce platform, focusing on the top 500 sportswear products over a two-and-a-half-year period, provide insights into the influence of various promotional strategies on user behavior [64]. Additionally, field tests using Microsoft's real online transaction data compared the performance of proposed control models against existing methods over a 14-week period, highlighting the importance of adaptive systems in managing user interactions [55].

### 5.5 Social Interactions and E-Commerce

Social interactions are pivotal in shaping e-commerce activities, influencing consumer behavior and enhancing user engagement. Integrating social networks into e-commerce platforms allows businesses to strategically leverage user interactions, transforming the consumer experience. The successful implementation of systems like AliMe MKG in the Taobao app exemplifies this integration, serving a vast number of customers daily and demonstrating the substantial impact of social interactions on e-commerce activities. This system highlights the importance of combining textual and visual data to enrich the customer experience through personalized interactions [49].

The Neural Rating Regression with Abstractive Tips Generation (NRT) model, capable of predicting ratings and generating meaningful tips, underscores the significance of social interactions in enhancing consumer satisfaction. By providing comprehensive user recommendations, this model fosters trust in e-commerce platforms [57]. Additionally, methodologies that process unstructured data rapidly and uncover detailed insights, as discussed by [54], inform better customer service strategies, reinforcing the critical role of social interactions in e-commerce.

Future research should focus on developing more dynamic e-commerce systems that can adapt to changing market demands and leverage new technologies for enhanced operational success. This includes exploring the semantic gap's impact on other e-commerce factors and its role in customer-to-customer communication [48]. Moreover, applying rationality pattern functions to real-world data could provide valuable insights into consumer trust and decision-making processes, further enhancing e-commerce platforms [47].

The potential for future developments to incorporate additional factors, such as manufacturing and storage costs, and to expand the system's applicability to a broader range of products and market conditions, is significant [64]. Furthermore, enhancing information sharing among decision parties and extending frameworks to address more complex fraud scenarios remain critical areas for future exploration [55].

## 6 Instructional Design and Digital Literacy

### 6.1 Principles of Instructional Design in Digital Literacy

Instructional design in digital literacy involves a comprehensive approach that combines digital, data, and AI literacy, fostering critical engagement in educational contexts [65]. This integration is crucial for preparing learners to effectively navigate complex digital landscapes. Frameworks that categorize these literacies highlight the necessity of a holistic digital literacy education.

A fundamental aspect of instructional design is embedding ethical guidelines and regulatory frameworks, particularly with the use of Large Language Models (LLMs) in persuasive contexts [3]. These frameworks ensure that learners not only gain technical skills but also develop the ethical understanding needed for responsible digital technology engagement.

Tailoring AI literacy training to specific demographics, such as older workers, by defining necessary competencies for AI technology use is vital [21]. This approach emphasizes the creation of instructional materials that are relevant and accessible to diverse learner groups.

Moreover, instructional design should translate complex machine learning insights into actionable educational strategies, facilitating the integration of digital literacy into teaching practices and enhancing student engagement [30]. Leveraging existing research on foundational information and digital literacy competencies can strengthen AI literacy [11], thus fostering a more cohesive digital literacy curriculum that meets learners' evolving needs.

Innovative instructional and assessment methods enable a nuanced understanding of student interactions with learning materials [66]. Such integration supports the development of adaptive instructional strategies that enhance engagement with digital content.

Adaptive feedback mechanisms are crucial in instructional design, influencing revision strategies and promoting engagement in writing tasks [25]. These mechanisms facilitate self-regulated learning by providing learners with tools and feedback to continuously refine their digital literacy skills.

### 6.2 Technological Integration and Digital Skill Enhancement

Incorporating technology into instructional design is key to enhancing digital skills, enabling learners to develop competencies necessary for navigating complex digital environments. Mobile technologies, for instance, offer significant opportunities for fostering self-regulation and collaborative learning, provided effective implementation strategies and learner engagement levels are maintained [7]. These technologies promote active engagement with digital content, enhancing the acquisition and application of digital skills.

Data-driven approaches enhance technology integration in instructional design by offering insights into consumer behavior and market dynamics. For example, using supply-side data to identify foreign webshops and estimate sales to Dutch consumers illustrates how data analytics can inform educational practices and enhance digital literacy [67]. By leveraging such data, educators can create instructional materials pertinent to learners in a globalized digital economy.

The integration of technology necessitates a focus on adaptive learning environments tailored to individual learner needs. These environments utilize advanced data analytics and human feedback to deliver personalized support, fostering self-regulated learning skills and allowing learners to cultivate digital competencies at their own pace. Integrating behavioral feedback from writing engagement analytics enhances student performance, particularly for those with lower self-regulated learning abilities. As AI tools become more prevalent in education, developing AI literacy alongside digital skills is essential for both students and educators to navigate this evolving landscape effectively [68, 69, 11, 13, 70]. This personalized approach is critical for fostering engagement and ensuring learners achieve their full potential in digital literacy.

As depicted in Figure 6, the integration of technology in education not only enhances digital skills but also emphasizes the development of adaptive learning environments and the promotion of critical thinking and problem-solving skills through AI literacy and self-regulated learning strategies. The integration of technology in instructional design should prioritize developing critical thinking and problem-solving skills, particularly through AI literacy and self-regulated learning strategies. As educators increasingly employ AI tools like ChatGPT, designing lesson plans that teach responsible technology use while enhancing digital skills and ethical understanding is vital. Additionally, leveraging computer-based learning environments can support individualized learning experiences, enabling students to navigate complex topics effectively while honing their metacognitive abilities [11, 12]. These competencies are essential for learners to utilize digital tools effectively and meet the challenges of the digital age. By embedding these skills within the instructional framework, educators can prepare learners for the demands of the modern workforce and society.

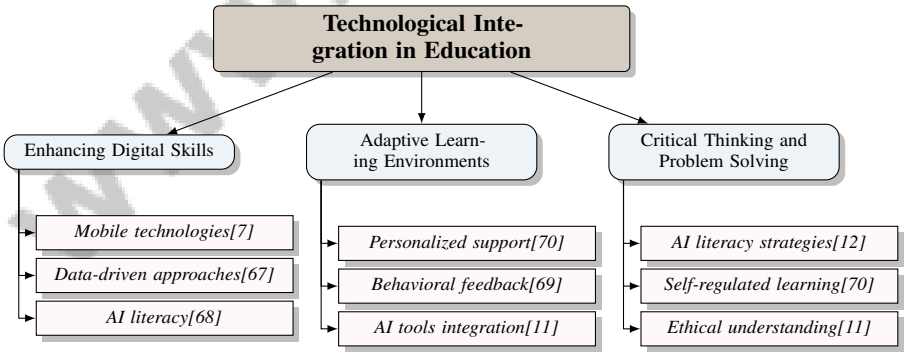


Figure 6: This figure illustrates the integration of technology in education, highlighting the enhancement of digital skills, the development of adaptive learning environments, and the promotion of critical thinking and problem-solving skills through AI literacy and self-regulated learning strategies.

### 6.3 Frameworks and Strategies for Digital Literacy Development

Frameworks and strategies for digital literacy development are crucial for equipping learners with the skills needed to navigate and engage with digital technologies effectively. The Unrestricted Policy-Guided Path Reasoning (UPGPR) framework, for example, enhances digital literacy through explainable recommendation systems that clarify available course options, facilitating informed

decision-making and personalized learning paths [71]. This underscores the importance of transparency and explainability in digital literacy initiatives, enabling learners to critically assess and select educational resources aligned with their goals.

Leveraging data-driven insights can significantly enhance digital literacy development. Utilizing existing administrative data in the supply-side approach to measuring cross-border internet purchases provides a more accurate reflection of consumer behaviors compared to traditional surveys [67]. Integrating these insights into instructional design allows educators to create targeted digital literacy programs addressing learners' specific needs and contexts.

Moreover, digital literacy development should incorporate adaptive learning environments responsive to individual learner requirements. These environments utilize real-time data to provide tailored feedback and support, empowering learners to progress at their own pace while effectively developing essential digital competencies. Integrating self-regulated learning strategies enhances student engagement and performance, particularly in reflective writing tasks, where combining analytical and human feedback has been shown to improve learning outcomes, especially for those with lower self-regulation skills [13, 70]. The integration of such adaptive systems is crucial for fostering engagement and ensuring learners can apply digital skills across diverse contexts.

### 6.4 Feedback and Reflective Practices in Digital Literacy

Feedback and reflective practices are essential components of digital literacy education, significantly enhancing learners' engagement and understanding of digital technologies. The integration of Learning Analytics (LA) into educational settings underscores the need for feedback mechanisms tailored to diverse learner requirements, as these systems enhance self-regulated learning skills critical for academic success and empower students and teachers to engage actively in the learning process. This approach ensures feedback is a dynamic process fostering meaningful interactions, ultimately leading to improved learning outcomes and performance [27, 13, 68, 32]. These mechanisms provide real-time insights into learners' progress, enabling personalized interventions that support the development of digital competencies.

The effectiveness of LA-based feedback relies on developing feedback literacy among both teachers and students, which involves interpreting and acting upon feedback and providing constructive feedback to peers. Training programs focused on LA-specific feedback literacy are essential for maximizing feedback's impact in digital literacy education [68]. Such programs should also address the design of LA systems, ensuring user-friendliness and the capacity to deliver meaningful insights facilitating reflective practices.

Reflective practices complement feedback by encouraging learners to critically evaluate their experiences and identify areas for improvement. These practices enhance comprehension of digital content and technologies, equipping students and educators with essential AI literacy and self-regulated learning strategies, thereby fostering lifelong learning and adaptability in an increasingly complex digital landscape [11, 58, 70, 35]. Engaging in reflective practices enables learners to develop metacognitive skills that enhance their ability to self-regulate and adapt their learning strategies to new challenges.

## 7 Higher Education and Digital Literacy

In higher education, embedding digital literacy is essential for student achievement and educator readiness. Teaching digital, data, and AI literacy effectively enables students to critically engage with technology and succeed in a dynamic digital environment. The following subsection explores the critical role of educator readiness in promoting these literacies, highlighting the importance of professional development and feedback mechanisms.

### 7.1 Educator Preparedness in Digital, Data, and AI Literacy

Educator readiness in digital, data, and AI literacy is crucial for equipping students with essential skills in a technology-driven environment. Teachers play a pivotal role in integrating these literacies into curricula, empowering students to critically engage with digital technologies. The Generative AI Literacy Test (GLAT), validated with higher education datasets, underscores the need for educators to possess comprehensive AI literacy to guide students effectively in navigating AI technologies [36].

Furthermore, educators must develop feedback literacy to enhance learning analytics (LA) effectiveness in supporting student learning. This involves interpreting and applying insights from LA systems to provide timely, constructive feedback, vital for fostering students' self-regulation [27]. Aligning learners' expectations with outcomes is essential, as students value timely feedback, privacy, and the ability to manage their learning through LA insights.

Professional development programs focused on digital, data, and AI literacy are essential for preparing educators to teach these competencies effectively. These programs should emphasize ethical considerations in teaching methodologies, equipping educators to navigate AI complexities while fostering AI literacy among faculty and students for responsible and effective tool use in learning environments [11, 15, 8, 65]. By cultivating a comprehensive understanding of these literacies, educators can better support students in acquiring critical skills for responsible digital engagement.

### 7.2 MOOCs and AI-Driven Recommendations

Massive Open Online Courses (MOOCs) have transformed digital literacy education by providing scalable, accessible global learning opportunities. AI-driven recommendation systems within MOOCs enhance learning by personalizing content delivery and supporting learner engagement. These systems use advanced algorithms to analyze learner data, offering tailored recommendations aligned with individual preferences and goals [71].

As illustrated in Figure 7, the hierarchical structure of MOOCs and AI-driven recommendations highlights key aspects such as personalized learning, skill development, and scalability and access. Each category emphasizes the integration of AI in MOOCs to enhance learning experiences and promote digital literacy. AI-driven recommendations create personalized learning pathways, enabling learners to navigate complex course offerings and select content that best suits their needs. Explainable recommendation systems enhance learner autonomy and decision-making by clarifying the rationale behind suggested courses and materials [71]. These systems empower learners to control their learning journeys, promoting digital literacy.

Moreover, integrating AI technologies in MOOCs fosters critical thinking and problem-solving skills, crucial components of digital literacy. By adapting course content to learners' evolving needs, AI-driven recommendations ensure educational experiences remain relevant and engaging. This adaptability is vital for sustaining learner motivation and enhancing digital competencies as students navigate the changing educational technology landscape. Effective self-regulated learning strategies improve performance and empower students to use digital tools responsibly and ethically, fostering deeper engagement and skill acquisition in a rapidly evolving environment [11, 25, 70].

Additionally, AI-driven recommendation systems enhance MOOCs' scalability by managing large volumes of learner data and providing personalized support at scale. This capability addresses the diverse needs of a global learner population, promoting equitable access to high-quality educational resources, fostering AI literacy among students and faculty, and supporting critical digital skills development necessary for navigating an increasingly complex educational landscape [11, 35, 9].

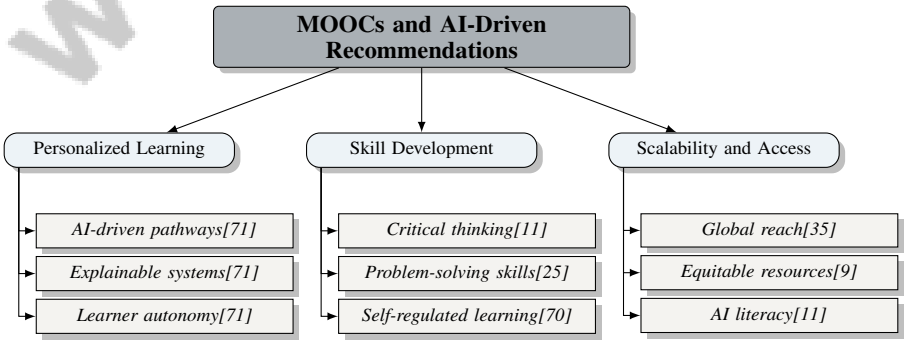


Figure 7: This figure illustrates the hierarchical structure of MOOCs and AI-Driven Recommendations, highlighting key aspects such as personalized learning, skill development, and scalability and access. Each category emphasizes the integration of AI in MOOCs to enhance learning experiences and promote digital literacy.

### 7.3 Learning Analytics and Feedback Mechanisms

Learning analytics (LA) and feedback mechanisms are pivotal in higher education, enhancing student engagement, learning outcomes, and instructional effectiveness. By integrating LA, educators can collect and analyze data on student interactions and performance, providing insights that inform personalized feedback and support [27]. This data-driven approach allows educators to tailor instructional strategies to diverse learner needs, fostering a more inclusive and effective learning environment.

LA is particularly valuable for identifying at-risk students and implementing timely interventions to support their academic success. By analyzing student data patterns, educators can detect early signs of disengagement or underperformance, enabling proactive measures [27]. This capability underscores LA's importance in promoting equitable access to educational resources and opportunities for all students.

Integrating feedback mechanisms with LA enhances the learning experience by providing students with actionable insights into their progress and areas for improvement. Aligning feedback with student expectations is crucial, ensuring learners receive the guidance needed to self-regulate their learning and achieve academic goals [27]. Using LA to inform feedback practices supports student learning and empowers educators to refine instructional approaches based on empirical evidence.

Cultivating feedback literacy among educators and students is vital for enhancing LA's effectiveness in higher education, encouraging active engagement in the feedback process, improving self-regulated learning skills for students, and facilitating informed teaching interventions for educators. This dual development maximizes data-driven feedback's impact and addresses cognitive, social-affective, and structural challenges in LA implementation [11, 13, 68]. Educators must be equipped to interpret and utilize LA insights effectively, while students should learn to act on feedback to enhance their learning. Professional development programs focusing on these competencies are crucial for fostering a culture of continuous improvement and innovation in higher education.

### 7.4 Digital Literacy for Late-Career Learners

Developing digital literacy for late-career learners is crucial for ensuring individuals nearing retirement have the skills to navigate an increasingly digitalized workplace and society. This demographic often faces unique challenges in acquiring digital and AI skills, necessitating targeted strategies to bridge knowledge gaps and enhance digital competencies [21].

Customized AI literacy training programs effectively enhance late-career workers' employability and adaptability. These programs address older employees' specific needs, equipping them with essential skills to navigate the evolving technological landscape, including understanding AI tools and their workplace applications. Research indicates tailored training significantly improves digital skills and fosters a more inclusive workforce, benefiting both individuals and organizations [11, 9, 21]. Such programs should focus on demystifying AI technologies and fostering practical understanding of how these tools can enhance work efficiency and personal productivity, alleviating apprehensions and increasing engagement among older learners.

Creating supportive learning environments that promote peer collaboration and mentorship can significantly enhance digital literacy development for late-career learners. Peer learning opportunities allow individuals to share experiences and insights, cultivating a community of practice that enhances continuous learning and develops essential self-regulated learning strategies. This collaborative approach is vital for adapting to emerging technologies, empowering participants to critically engage with digital tools and fostering a deeper understanding of their applications in educational contexts. Such environments encourage integrating AI literacy and digital skills, equipping learners to navigate modern learning landscapes effectively [11, 70, 12].

Additionally, leveraging flexible learning platforms that accommodate late-career learners' varied schedules and learning paces is essential. Online courses and modular learning formats offer crucial flexibility, allowing learners to access resources and complete training at their convenience. This flexibility fosters self-regulated learning (SRL), critical for success in online education. SRL involves planning, monitoring, and reflecting on one's learning processes, enabling learners to tailor their educational experiences to individual needs. Integrating personalized course recommendation systems can further enhance the learning experience by guiding students toward relevant resources, supporting

their autonomy and engagement in the learning process [71, 11, 72, 12, 29]. This approach not only enhances accessibility but also allows learners to customize their educational experiences to their specific needs and interests.

# 8 Conclusion

## 8.1 Future Directions and Research Opportunities

Advancing AI literacy within academic environments requires structured programs that integrate both technical and ethical aspects, fostering continuous learning and critical thinking in response to the dynamic nature of higher education. The focus should be on developing curricula that adapt to these evolving demands and enhance user-level personalization through innovative optimization methods. In the realm of self-regulated learning (SRL), refining data collection and analytical methodologies is essential to deepen the understanding of SRL's implementation in diverse educational settings. Longitudinal research on teacher competency development and its impact on student SRL is vital, alongside evaluating the adaptability and effectiveness of tools like FlippED across cultural contexts. Training educators to effectively incorporate SRL strategies is crucial for student success.

The role of learning analytics (LA) in education necessitates further exploration, emphasizing the importance of feedback literacy and the design of LA systems that promote meaningful dialogue. Future research should focus on developing AI applications that cater to individual learner identities, thereby enhancing motivation and learner agency. In the e-commerce domain, improving data quality and leveraging structured data in natural language processing remain key areas for development. Investigating the factors influencing student cognition in online graduate programs will provide insights into enhancing educational outcomes.

Research should also prioritize the evaluation of hybrid models and the long-term impacts of learning interventions, particularly in relation to GenAI literacy and the application of chatbot technologies in varied educational contexts. Exploring advanced methodologies such as tensor factorization and custom tree-based models for interpretability, alongside addressing challenges like the cold-start problem, offers promising research avenues. Expanding predictive methodologies to encompass broader geographic regions could yield valuable insights for cross-border e-commerce. Finally, assessing the long-term efficacy of feedback interventions across different educational contexts remains a critical area for further investigation.

## References


[1] Daswin De Silva, Shalinka Jayatilleke, Mona El-Ayoubi, Zafar Issadeen, Harsha Moraliyage, and Nishan Mills. The human-centred design of a universal module for artificial intelligence literacy in tertiary education institutions. *Machine Learning and Knowledge Extraction*, 6(2):1114–1125, 2024.

[2] Carmen Yot-Domínguez and Carlos Marcelo. University students' self-regulated learning using digital technologies. *International Journal of Educational Technology in Higher Education*, 14:1–18, 2017.

[3] Alexander Rogiers, Sander Noels, Maarten Buyl, and Tijl De Bie. Persuasion with large language models: a survey, 2024.

[4] Deborah L Butler. Qualitative approaches to investigating self-regulated learning: Contributions and challenges. In *Using qualitative methods to enrich understandings of self-regulated learning*, pages 59–63. Routledge, 2023.

[5] Sung-Hee Jin, Kowoon Im, Mina Yoo, Ido Roll, and Kyoungwon Seo. Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, 20(1):37, 2023.

[6] Marissa Keech and Ashok Goel. Why are some online educational programs successful? student cognition and success, 2022.

[7] Olga Viberg and Agnes Kukulska-Hulme. Fostering learners' self-regulation and collaboration skills and strategies for mobile language learning beyond the classroom, 2021.

[8] Mavis Brew, Stephen Taylor, Rachel Lam, Leo Havemann, and Chrissi Nerantzi. Towards developing ai literacy: three student provocations on ai in higher education. *Asian Journal of Distance Education*, 18(2):1–11, 2023.

[9] Yohan Hwang, Jang Ho Lee, and Dongkwang Shin. What is prompt literacy? an exploratory study of language learners' development of new literacy skill using generative ai. *arXiv preprint arXiv:2311.05373*, 2023.

[10] Christian Montag, Preslav Nakov, and Raian Ali. On the need to develop nuanced measures assessing attitudes towards ai and ai literacy in representative large-scale samples. *AI & SOCIETY*, pages 1–2, 2024.

[11] Jamillah Scott-Branch, Robert Laws, and Paschalia Terzi. The intersection of ai, information and digital literacy: Harnessing chatgpt and other generative tools to enhance teaching and learning. 2023.

[12] Roger Azevedo. Using hypermedia as a metacognitive tool for enhancing student learning? the role of self-regulated learning. In *Computers as Metacognitive Tools for Enhancing Learning*, pages 199–209. Routledge, 2018.

[13] Wannapon Suraworachet, Qi Zhou, and Mutlu Cukurova. Impact of combining human and analytics feedback on students' engagement with, and performance in, reflective writing tasks, 2022.

[14] Alexander Nussbaumer, Milos Kravcik, Dominik Renzel, Ralf Klamma, Marcel Berthold, and Dietrich Albert. A framework for facilitating self-regulation in responsive open learning environments, 2014.

[15] Ricardo Limongi and Carla Bonato Marcolin. Ai literacy research: frontier for high-impact research and ethics, 2024.

[16] Yaoke Wang, Yun Zhu, Xintong Bao, Wenqiao Zhang, Suyang Dai, Kehan Chen, Wenqiang Li, Gang Huang, Siliang Tang, and Yueting Zhuang. Meta-reflection: A feedback-free reflection learning framework, 2024.

[17] Chi-Jung Sui, Miao-Hsuan Yen, and Chun-Yen Chang. Investigating effects of perceived technology-enhanced environment on self-regulated learning: Beyond p-values, 2023.

[18] Pascal Klein, Lana Ivanjek, Merten Nikolay Dahlkemper, Katarina Jeličić, Marie-Annette Geyer, Stefan Küchemann, and Ana Susac. Studying physics during the covid-19 pandemic: Student assessments of learning achievement, perceived effectiveness of online recitations, and online laboratories, 2020.

[19] Ernesto Panadero. A review of self-regulated learning: Six models and four directions for research. *Frontiers in psychology*, 8:422, 2017.

[20] Asif Perwej. On applying neuro - computing in e-com domain, 2012.

[21] Krish Chetty. Ai literacy for an ageing workforce: Leveraging the experience of older workers. *OBM Geriatrics*, 7(3):1–17, 2023.

[22] Mack Sweeney, Huzefa Rangwala, Jaime Lester, and Aditya Johri. Next-term student performance prediction: A recommender systems approach, 2016.

[23] Norbert Pengel, Anne Martin, Roy Meissner, Tamar Arndt, Alexander Tobias Neumann, Peter de Lange, and Heinz-Werner Wollersheim. Teccobot: Technology-aided support for self-regulated learning, 2021.

[24] Feng Tian, Jia Yue, Kuo ming Chao, Buyue Qian, Nazaraf Shah, Longzhuang Li, Haiping Zhu, Yan Chen, Bin Zeng, and Qinghua Zheng. Modeling e-learners' cognitive and metacognitive strategy in comparative question solving, 2019.

[25] Luca Mouchel, Thiemo Wambsganss, Paola Mejia-Domenzain, and Tanja Käser. Understanding revision behavior in adaptive writing support systems for education, 2023.

[26] Justin Filippou, Christopher Cheong, and France Cheong. Combining the fogg behavioural model and hook model to design features in a persuasive app to improve study habits, 2016.

[27] Saša Brdnik, Boštjan Šumak, and Vili Podgorelec. Aligning learners' expectations and performance by learning analytics systemwith a predictive model, 2022.

[28] Nancy E Perry, Karen O VandeKamp, Louise K Mercer, and Carla J Nordby. Investigating teacher—student interactions that foster self-regulated learning. In *Using Qualitative Methods To Enrich Understandings of Self-regulated Learning*, pages 5–15. Routledge, 2023.

[29] R. Cerezo, A. Bogarin, M. Esteban, and C. Romero. Process mining for self-regulated learning assessment in e-learning, 2024.

[30] Paola Mejia-Domenzain, Eva Laini, Seyed Parsa Neshaei, Thiemo Wambsganss, and Tanja Käser. Visualizing self-regulated learner profiles in dashboards: Design insights from teachers, 2023.

[31] Binnur Ergen and Sedat Kanadlı. The effect of self-regulated learning strategies on academic achievement: A meta-analysis study. *Eurasian Journal of Educational Research*, 17(69):55–74, 2017.

[32] Mohamed Amine Chatti, Volkan Yücepur, Arham Muslim, Mouadh Guesmi, and Shoeb Joarder. Designing theory-driven analytics-enhanced self-regulated learning applications, 2023.

[33] Stella Vosniadou. Bridging secondary and higher education. the importance of self-regulated learning. *European Review*, 28(S1):S94–S103, 2020.

[34] Yves Karlen, Silke Hertel, and Carmen Nadja Hirt. Teachers' professional competences in self-regulated learning: An approach to integrate teachers' competences as self-regulated learners and as agents of self-regulated learning in a holistic manner. In *Frontiers in Education*, volume 5, page 159. Frontiers Media SA, 2020.

[35] Daniella Taranto and Michael T Buchanan. Sustaining lifelong learning: A self-regulated learning (srl) approach. *Discourse and Communication for Sustainable Education*, 11(1):5–15, 2020.

[36] Yueqiao Jin, Roberto Martinez-Maldonado, Dragan Gašević, and Lixiang Yan. Glat: The generative ai literacy assessment test, 2024.

[37] Chester Palen-Michel, Ruixiang Wang, Yipeng Zhang, David Yu, Canran Xu, and Zhe Wu. Investigating llm applications in e-commerce, 2024.

[38] Yangning Li, Shirong Ma, Xiaobin Wang, Shen Huang, Chengyue Jiang, Hai-Tao Zheng, Pengjun Xie, Fei Huang, and Yong Jiang. Ecomgpt: Instruction-tuning large language models with chain-of-task tasks for e-commerce, 2023.

[39] Shuyan Zhou, Frank F. Xu, Hao Zhu, Xuhui Zhou, Robert Lo, Abishek Sridhar, Xianyi Cheng, Tianyue Ou, Yonatan Bisk, Daniel Fried, Uri Alon, and Graham Neubig. Webarena: A realistic web environment for building autonomous agents, 2024.

[40] Andrea Papenmeier, Dagmar Kern, Daniel Hienert, Alfred Sliwa, Ahmet Aker, and Norbert Fuhr. Dataset of natural language queries for e-commerce, 2023.

[41] Yizhou Fan, Luzhen Tang, Huixiao Le, Kejie Shen, Shufang Tan, Yueying Zhao, Yuan Shen, Xinyu Li, and Dragan Gašević. Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance, 2024.

[42] Jiao Chen, Luyi Ma, Xiaohan Li, Nikhil Thakurdesai, Jianpeng Xu, Jason H. D. Cho, Kaushiki Nag, Evren Korpeoglu, Sushant Kumar, and Kannan Achan. Knowledge graph completion models are few-shot learners: An empirical study of relation labeling in e-commerce with llms, 2023.

[43] Siddharth D Jaiswal, Abhisek Dash, Nitika Shroff, Yashwanth Babu Vunnam, Saptarshi Ghosh, and Animesh Mukherjee. Auditing the grid-based placement of private label products on e-commerce search result pages, 2024.

[44] Lin Gao, Jing Lu, Zekai Shao, Ziyue Lin, Shengbin Yue, Chiokit Ieong, Yi Sun, Rory James Zauner, Zhongyu Wei, and Siming Chen. Fine-tuned large language model for visualization system: A study on self-regulated learning in education, 2024.

[45] Yueqiao Jin, Kaixun Yang, Lixiang Yan, Vanessa Echeverria, Linxuan Zhao, Riordan Alfredo, Mikaela Milesi, Jie Fan, Xinyu Li, Dragan Gašević, and Roberto Martinez-Maldonado. Chatting with a learning analytics dashboard: The role of generative ai literacy on learner interaction with conventional and scaffolding chatbots, 2024.

[46] Malak Mashaabi, Areej Alotaibi, Hala Qudaih, Raghad Alnashwan, and Hend Al-Khalifa. Natural language processing in customer service: A systematic review, 2022.

[47] Dipankar Das. Measurement of trustworthiness of the online reviews, 2023.

[48] Carlos A. Rodriguez-Diaz, Sergio Jimenez, Daniel Bejarano, Julio A. Bernal-Chávez, and Alexander Gelbukh. Semantics between customers and providers: The relation between product descriptions, reviews, and customer satisfaction in e-commerce, 2022.

[49] Guohai Xu, Hehong Chen, Feng-Lin Li, Fu Sun, Yunzhou Shi, Zhixiong Zeng, Wei Zhou, Zhongzhou Zhao, and Ji Zhang. Alime mkg: A multi-modal knowledge graph for live-streaming e-commerce, 2021.

[50] Archit Bansal, Kunal Banerjee, and Abhijnan Chakraborty. These deals won't last! longevity, uniformity and bias in product badge assignment in e-commerce platforms, 2022.

[51] Bo Peng, Xinyi Ling, Ziru Chen, Huan Sun, and Xia Ning. ecellm: Generalizing large language models for e-commerce from large-scale, high-quality instruction data, 2024.

[52] Carlos Carrion, Zenan Wang, Harikesh Nair, Xianghong Luo, Yulin Lei, Xiliang Lin, Wenlong Chen, Qiyu Hu, Changping Peng, Yongjun Bao, and Weipeng Yan. Blending advertising with organic content in e-commerce: A virtual bids optimization approach, 2021.

[53] Ziad Hmwd A Almtiri, Shah J Miah, and Nasimul Noman. Application of e-commerce technologies in accelerating the success of sme operation, 2022.

[54] Andry Alamsyah, Nurlisa Laksmiani, and Lies Anisa Rahimi. A core of e-commerce customer experience based on conversational data using network text methodology, 2021.

[55] Junxuan Li, Yung wen Liu, Yuting Jia, and Jay Nanduri. Discriminative data-driven self-adaptive fraud control decision system with incomplete information, 2019.

[56] Suhas Ranganath. Leveraging catalog knowledge graphs for query attribute identification in e-commerce sites, 2018.

[57] Piji Li, Zihao Wang, Zhaochun Ren, Lidong Bing, and Wai Lam. Neural rating regression with abstractive tips generation for recommendation, 2017.

[58] Miguel Alves Gomes, Philipp Meisen, and Tobias Meisen. Towards lifelong learning embeddings: An algorithmic approach to dynamically extend embeddings, 2024.

[59] Jie Huang, Yifan Gao, Zheng Li, Jingfeng Yang, Yangqiu Song, Chao Zhang, Zining Zhu, Haoming Jiang, Kevin Chen-Chuan Chang, and Bing Yin. Ccgen: Explainable complementary concept generation in e-commerce, 2023.

[60] Rahul Radhakrishnan Iyer, Rohan Kohli, and Shrimai Prabhumoye. Modeling product search relevance in e-commerce, 2020.

[61] Qian Yu, Lidong Bing, Qiong Zhang, Wai Lam, and Luo Si. Review-based question generation with adaptive instance transfer and augmentation, 2020.

[62] Ravi Bapna, Paulo Goes, Ram Gopal, and James R. Marsden. Moving from data-constrained to data-enabled research: Experiences and challenges in collecting, validating and analyzing large-scale e-commerce data, 2006.

[63] Mahdi H. Miraz and Marie Haikel-Elsabeh. Analysis of users' behaviour and adoption trends of social media payment platforms, 2020.

[64] Chenyang Zhang, Xiyuan Wang, Chuyi Zhao, Yijing Ren, Tianyu Zhang, Zhenhui Peng, Xiaomeng Fan, and Quan Li. Promotionlens: Inspecting promotion strategies of online e-commerce via visual analytics, 2022.

[65] Moritz Kreinsen and Sandra Schulz. Towards the triad of digital literacy, data literacy and ai literacy in teacher education–a discussion in light of the accessibility of novel generative ai. 2023.

[66] Kyle M. Whitcomb, Matthew W. Guthrie, Chandralekha Singh, and Zhongzhou Chen. Toward more accurate measurement of the impact of online instructional design on students' ability to transfer physics problem-solving skills, 2021.

[67] Q. A. Meertens, C. G. H. Diks, H. J. van den Herik, and F. W. Takes. A data-driven supply-side approach for measuring cross-border internet purchases, 2018.

[68] Yi-Shan Tsai. Why feedback literacy matters for learning analytics, 2023.

[69] Philip H Winne. Learning analytics for self-regulated learning. *Handbook of learning analytics*, 754:241–249, 2017.

[70] Lilian Anthonysamy, Koo Ah Choo, and Hew Soon Hin. Investigating self-regulated learning strategies for digital learning relevancy. *Malaysian Journal of Learning and Instruction*, 18(1):29–64, 2021.

[71] Jibril Frej, Neel Shah, Marta Knežević, Tanya Nazaretsky, and Tanja Käser. Finding paths for explainable mooc recommendation: A learner perspective, 2023.

[72] Mohammad Khalil. Molam: A mobile multimodal learning analytics conceptual framework to support student self-regulated learning, 2020.

**Disclaimer:**

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.