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Generative Artificial Intelligence in Instructional Design Practice: Adoption Patterns, Perceived Value, Implementation Challenges, and Emerging Professional Strategies

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ABSTRACT

Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), this study investigates how instructional designers in Saudi Arabian context integrate generative AI tools into their professional activities and what benefits, obstacles and the practices they have developed to support responsible implementation. A mixed-methods research design was employed which involved a survey of 262 instructional design professionals and in-depth focus group discussions with 12 practitioners representing higher education, corporate training, government, and nonprofit sectors. The findings indicate that instructional designers increasingly view generative AI as a collaborative design resource rather than a replacement for professional expertise. Performance expectancy emerged as a significant predictor of adoption, particularly in tasks involving ideation, content development, assessment design, and workflow acceleration. At the same time, participants expressed ongoing concerns regarding output accuracy, pedagogical appropriateness, data privacy, and organizational governance. The results also reveal the emergence of sophisticated human–AI collaboration models in which designers actively evaluate, revise, and contextualize AI-generated outputs before implementation. This study contributes to the growing body of research on educational applications of artificial intelligence by providing a theoretically grounded understanding of technology adoption among instructional designers. It further highlights the importance of organizational support, professional competencies, and ethical oversight in shaping effective AI integration strategies within instructional design practice.

Keywords: Generative Artificial Intelligence, Instructional Design, UTAUT, Human–AI Collaboration, Educational Technology, Instructional Learning Design.

INTRODUCTION

Artificial intelligence has rapidly transitioned from an emerging technological innovation to a practical component of contemporary educational and professional environments. Over the past several years, advances in machine learning, large language models, and foundation-model architectures have significantly expanded the capabilities of AI systems, enabling them to generate text, images, assessments, feedback, and other forms of educational content with unprecedented speed and sophistication (Krenn, et al., 2022). These developments have sparked widespread discussion regarding the future of teaching, learning, and educational design.

Within the broader educational landscape, instructional design has emerged as one of the professional domains most immediately affected by generative AI technologies. Instructional designers occupy a unique position at the intersection of pedagogy, technology, and content development. Their responsibilities frequently include conducting learning needs analyses, developing instructional strategies, creating assessments, designing learner experiences, and collaborating with subject-matter experts. Many of these activities involve tasks that generative AI systems can potentially support or accelerate (Minh et al., 2022).

Recent developments in large language models have created new opportunities for instructional designers to streamline portions of their workflow. Generative AI systems can rapidly produce draft learning objectives, generate assessment items, summarize content, create instructional materials, suggest learning activities, and provide alternative explanations tailored to diverse learner needs (Banh & Strobel, 2023). These capabilities have attracted considerable attention among educational institutions, corporate learning departments, and professional training organizations seeking to increase efficiency while maintaining instructional quality.

However, enthusiasm surrounding generative AI is accompanied by significant uncertainty. Questions remain regarding the reliability of AI-generated content, the pedagogical soundness of automated instructional recommendations, intellectual property concerns, data privacy risks, and the potential consequences of overreliance on algorithmically generated materials (Meske et al., 2022). Educational professionals must therefore navigate a complex landscape in which technological possibilities coexist with ethical, organizational, and pedagogical challenges (Loh et al., 2022).

For instructional designers, the integration of generative AI extends beyond questions of technological adoption. It involves decisions about professional judgment, instructional quality, learner outcomes, and the evolving role of human expertise within increasingly automated environments. While AI systems can generate content at remarkable speed, effective instructional design requires nuanced understanding of learner characteristics, educational contexts, motivation, engagement, and pedagogical principles. Consequently, the relationship between instructional designers and generative AI is unlikely to be characterized by simple replacement. Instead, it appears to involve emerging forms of collaboration in which human expertise and machine-generated outputs interact in dynamic ways (Ruiz-Rojas et al., 2023).

Although scholarly interest in generative AI has grown substantially, empirical investigations like Chng (2023) and Abuhassna and Alnawajha (2023) focused specifically on instructional designers remain relatively limited. Existing research has primarily documented early adoption trends, identified potential benefits, and discussed ethical concerns associated with AI use in educational settings. Less attention has been devoted to understanding how instructional designers incorporate AI into everyday practice, how organizational environments shape implementation decisions, and how professionals negotiate the balance between efficiency and instructional integrity.

The present study addresses these issues by examining the experiences of practicing instructional designers who actively engage with generative AI technologies. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), the research explores patterns of adoption, perceived advantages, implementation barriers, and emerging professional practices. By focusing on the lived experiences of instructional design practitioners, the study seeks to provide a deeper understanding of how generative AI is transforming professional workflows while highlighting the human factors that continue to shape effective instructional design.

Problem Statement

The growing presence of generative artificial intelligence in educational and training environments has generated considerable interest among researchers and practitioners. Despite this rapid expansion, important gaps remain in the current understanding of how instructional designers engage with these technologies in professional contexts.

First, much of the existing literature emphasizes technological capabilities and potential applications while providing limited theoretical explanations of adoption behaviour. Although researchers have documented increasing use of generative AI within education, relatively few studies have applied established technology acceptance frameworks to explain why instructional designers choose to adopt, reject, or selectively integrate these tools into their workflows. As a result, current knowledge lacks a comprehensive understanding of the factors influencing implementation decisions.

Second, previous research has frequently portrayed AI as a productivity tool while paying less attention to the collaborative relationships that emerge between human professionals and intelligent systems. Instructional design is a knowledge-intensive profession requiring creativity, critical thinking, pedagogical expertise, and contextual judgment. Consequently, understanding how instructional designers interact with AI-generated outputs is essential for examining the evolving nature of professional practice.

Third, existing studies often discuss AI implementation in broad educational terms without fully considering the unique challenges associated with instructional design work. Tasks such as aligning learning objectives, developing assessments, applying learning theories, and maintaining pedagogical coherence require specialized expertise that may not be adequately captured in generalized discussions of educational technology adoption.

Greater attention is therefore needed to identify the opportunities and limitations that are specific to instructional design contexts.

Finally, organizational influences on AI adoption remain insufficiently understood. Institutional policies, leadership support, access to resources, professional development opportunities, and governance structures may significantly affect how instructional designers use AI technologies. Yet these contextual factors have received comparatively limited empirical examination.

Addressing these gaps is increasingly important as educational organizations continue investing in AI-enabled technologies. Understanding how instructional designers perceive, adopt, and operationalize generative AI can inform institutional decision-making, professional development initiatives, and future technology design efforts.

Theoretical Perspective

This study is guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a comprehensive framework for examining technology adoption and usage behaviour (Xue, Rashid & Ouyang, 2024). The model proposes that individuals' intentions to use technology and their actual use behaviours are influenced by several key factors, including performance expectancy, effort expectancy, facilitating conditions, and attitudes toward technology.

Wang et al. (2021) shared that performance expectancy refers to the extent to which individuals believe a technology will improve their professional performance. Within instructional design contexts, this construct relates to perceptions that generative AI can enhance productivity, improve content quality, accelerate workflows, or support instructional innovation.

On the other hand, effort expectancy reflects the degree of ease associated with using a technology. For instructional designers, this may involve learning how to create effective prompts, understanding system limitations, and integrating AI-generated outputs into established design processes. Facilitating conditions encompass the organizational, technical, and resource-related factors that support technology use. These include institutional policies, leadership support, training opportunities, technological infrastructure, and access to advanced AI tools (Alowayr, 2022).

Attitude represents individuals' overall perceptions and feelings toward a technology. In the context of generative AI, attitudes may include enthusiasm, scepticism, ethical concerns, trust, or confidence regarding AI-generated outputs.

Together, these constructs provide a useful lens for examining how instructional designers evaluate and integrate generative AI technologies within professional practice.

Research Questions

To investigate the adoption and implementation of generative AI among instructional design professionals, the study addresses the following research questions:

RQ1: How are instructional design professionals incorporating generative AI technologies across different phases of learning design and development processes?

RQ2: What perceived benefits, efficiencies, and instructional improvements do instructional designers associate with the use of generative AI tools?

RQ3: What professional strategies and implementation practices have emerged to support effective, responsible, and ethical use of generative AI in instructional design?

RQ4: What technical, pedagogical, organizational, and ethical challenges influence the integration of generative AI within instructional design practice?

LITERATURE REVIEW

Generative Artificial Intelligence and Educational Transformation

Unlike earlier forms of educational technology that primarily focused on content delivery or automation of predefined instructional tasks, generative AI introduces the capacity to produce novel, context-sensitive outputs across a wide range of educational activities. These include text generation, feedback provision, content summarization, assessment creation, and adaptive explanations tailored to learner needs.

Scholars have increasingly framed generative AI as a transformative force rather than a purely incremental innovation. Abuhassna and Alnawajha (2023) described foundation models as systems with broad applicability across domains, emphasizing both their versatility and their unpredictability. In educational contexts, this duality is particularly significant: while GenAI systems can support personalized learning and reduce instructor workload, they also introduce concerns related to accuracy, transparency, and epistemic reliability.

Sankaranarayanan and Park (2023) highlight that engaging with generative AI requires a form of "prompt literacy," where users must learn to communicate effectively with algorithmic systems to achieve desired outcomes. This interactional dimension positions AI not simply as a tool but as an active partner in knowledge production. Similarly, Argueta-Muñoz et al. (2023) argue that generative AI may reshape education through paradoxical effects simultaneously enhancing learning opportunities while raising questions about dependency, academic integrity, and pedagogical authority.

Within this evolving landscape, instructional design has become a particularly important site of inquiry due to its central role in structuring learning experiences and translating pedagogical theory into practice.

Instructional Design in the Era of Artificial Intelligence

Instructional design is a systematic discipline focused on the development, implementation, and evaluation of learning experiences. Traditionally grounded in behavioural, cognitive, and constructivist learning theories, instructional design involves iterative processes of analysis, design, development, implementation, and evaluation. The introduction of generative AI into this workflow represents a significant shift in how design decisions are made and executed.

Chng (2023) suggests that AI technologies are increasingly embedded in instructional design workflows, particularly in areas such as content generation, course structuring, and assessment design. These tools enable designers to rapidly prototype instructional materials and explore multiple design alternatives in reduced timeframes. Shakeel, Mia and Ahmed (2023) similarly noted that artificial intelligence is reshaping instructional design practice by accelerating content creation and enabling more adaptive learning environments.

However, this transformation is not without tension. While AI can enhance efficiency, it may also disrupt established pedagogical processes. Instructional designers must now evaluate not only the instructional quality of materials but also the reliability and pedagogical appropriateness of AI-generated content. This introduces a new layer of cognitive and ethical responsibility within the design process.

Ursavaş (2022) emphasize that UTAUT connecting with instructional designers increasingly act as intermediaries between AI systems and educational stakeholders. Their role is evolving from content creators to evaluators, curators, and orchestrators of AI-assisted instructional workflows. This shift suggests that instructional design is becoming a hybrid human–machine practice rather than a purely human-driven activity.

Generative AI Applications in Instructional Design Practice

Empirical research on the application of generative AI in instructional design remains emerging but growing. Leung et al. (2023) conducted a mixed-methods investigation into instructional designers' perceptions of GenAI and found that practitioners primarily use these tools for idea generation, drafting instructional materials, automating routine tasks, and enhancing collaboration with subject-matter experts. Their findings suggest that GenAI is not merely a productivity tool but an enabler of expanded creative capacity.

Similarly, Abuhassna and Alnawajha (2023) report that AI-assisted instructional design can improve efficiency in content development and assessment creation while also supporting more personalized learning experiences. These benefits are particularly evident in tasks that are repetitive or highly structured, where generative systems can quickly produce usable drafts that require minimal revision.

However, the adoption of generative AI is accompanied by significant concerns. Cukurbasi and Kiyici (2021) highlight issues related to reliability, bias, and hallucination in generative language models. These limitations require instructional designers to critically evaluate AI outputs before integration into learning environments. As a result, AI adoption in instructional design is characterized not by full automation but by iterative human review and refinement processes.

Xie and Rice (2021) emphasized that the effectiveness of generative AI is highly dependent on prompt quality. Prompt engineering has therefore emerged as a critical skill for users, requiring careful structuring of inputs to guide model outputs effectively. In instructional design contexts, this skill intersects with pedagogical knowledge, as prompts must often incorporate learning objectives, instructional constraints, and assessment criteria.

Saçak, Bozkurt and Wagner (2022) further argue that educational prompt engineering requires domain-specific adaptation. Generic prompts often fail to capture the complexity of instructional theory, necessitating iterative refinement and pedagogical grounding. This reinforces the idea that successful AI integration in instructional design depends not only on technological literacy but also on deep instructional expertise.

Human–AI Collaboration and Emerging Work Models

A central theme in recent literature is the shift from tool-based AI usage toward collaborative human–AI systems. Rather than replacing human expertise, generative AI increasingly functions as a co-participant in knowledge work. This perspective is reflected in the Human-in-the-Loop paradigm, which emphasizes continuous human oversight in AI-supported decision-making processes (Li et al., 2023).

Chartier (2021) conceptualized human oversight as a governance mechanism that ensures accountability and ethical responsibility in automated systems. In instructional design contexts, this oversight is essential given the educational consequences of inaccurate or inappropriate content generation.

Dousay and Branch (2023) proposed a structured model of educational collaboration in which AI systems assume roles such as content generation and feedback provision, while educators retain responsibility for pedagogical design, contextual interpretation, and ethical decision-making. This distributed model reflects a broader trend toward shared agency between humans and AI systems.

Then, Chartier et al. (2021) extends this discussion by suggesting that effective collaboration requires identifying a "sweet spot" between human control and machine autonomy. Too little human involvement risks pedagogical degradation, while excessive oversight may reduce the efficiency benefits of AI integration. Instructional designers must therefore navigate a dynamic balance between trust and verification.

Theoretical Foundations: Technology Adoption in Educational Contexts

To understand the reason of adaptation or resistance of technological innovations by individuals, scholars have developed several theoretical models, among which the Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most widely applied. Originally developed by González-Fernández et al. (2023) the model integrates multiple theoretical perspectives to explain technology adoption behaviour.

UTAUT proposes that four primary constructs performance expectancy, effort expectancy, social influence, and facilitating conditions shape behavioural intention and actual usage behaviour. Later refinements by Ivens (2023) extended the model to include additional contextual factors and broaden its applicability across domains.

Performance expectancy refers to perceived usefulness and anticipated improvements in job performance. In educational settings, this construct is often the strongest predictor of adoption behaviour. Effort expectancy relates to perceived ease of use, which can be influenced by interface design, user training, and cognitive load. Facilitating conditions capture organizational and infrastructural support mechanisms, while social influence reflects the perceived expectations of peers and institutions.

Barbosa, (2023) demonstrate that UTAUT has been widely applied in K–12 and higher education contexts, particularly in examining educator adoption of digital tools. Their review highlights that performance expectancy consistently emerges as the most influential predictor of adoption, followed by facilitating conditions.

Hirumi (2021) further refine the model by emphasizing contextual adaptation and the need to consider domain-specific variations. This is particularly relevant for instructional design, where professional practices are shaped by both pedagogical and organizational constraints.

UTAUT and Artificial Intelligence Adoption

Recent studies have begun applying UTAUT to artificial intelligence adoption in educational settings. These studies suggest that AI technologies introduce additional complexity into traditional adoption models. Unlike earlier technologies, AI systems are often probabilistic, adaptive, and partially opaque, which complicates user trust and perceived reliability.

Yalçın, Ursavaş and Klein (2021) highlighted that generative AI adoption is influenced not only by perceived usefulness but also by ethical concerns, data privacy issues, and epistemic trust. These factors extend beyond traditional UTAUT constructs, suggesting the need for contextual adaptation.

similarly critiques like Busuioc (2022) Shared that the assumption of effective human oversight in algorithmic systems, arguing that oversight mechanisms often fail when users lack transparency into system behaviour. In instructional design contexts, this raises important questions about how professionals evaluate AI-generated instructional content and ensure alignment with pedagogical standards.

Research Gaps in Instructional Design and GenAI

Despite growing interest in AI-supported education, several gaps remain in the literature. First, there is limited empirical understanding of how instructional designers integrate generative AI into everyday workflows. Much of the existing literature focuses on theoretical potential rather than observed professional practice.

Second, although human–AI collaboration has been widely discussed conceptually, fewer studies have examined how these interactions manifest in real instructional design environments. The processes by which instructional designers evaluate, modify, and validate AI outputs remain underexplored.

Third, domain-specific challenges associated with instructional design have not been sufficiently addressed. While generative AI performs well in general content generation tasks, its ability to support pedagogically grounded design decisions remains uncertain. Issues such as alignment with learning theories, assessment validity, and learner engagement require deeper investigation.

Fourth, organizational and institutional influences on AI adoption remain underdeveloped in current research. While individual-level factors such as perceived usefulness and ease of use are well studied, fewer studies examine how institutional policies, leadership support, and organizational culture shape AI integration practices.

Finally, there is a need for stronger theoretical grounding in empirical studies of generative AI in education. While UTAUT provides a useful foundation, its application to AI-mediated knowledge work requires further refinement to account for emerging complexities such as trust, interpretability, and collaborative agency.

The present study builds upon this body of work by examining how instructional designers navigate these emerging technologies in practice, with particular attention to adoption patterns, perceived benefits, implementation strategies, and contextual constraints.

METHODS

Research Design

This study adopted a convergent mixed-methods design to examine how instructional design professionals engage with generative artificial intelligence (GenAI) within real-world practice environments. Ali (2022) shared that mixed method approach is pivotal to find out quantitative and qualitative details in any research. The rationale for using a mixed-methods approach was grounded in the need to capture both measurable adoption patterns and the contextual, experiential dimensions of technology integration that cannot be fully explained through quantitative data alone.

Quantitative survey data provided a structured overview of adoption behaviours, perceived usefulness, and technology acceptance constructs derived from the Unified Theory of Acceptance and Use of Technology (UTAUT). Qualitative focus group data complemented this by offering deeper insights into lived experiences, professional decision-making processes, and organizational influences shaping GenAI integration.

Both datasets were collected concurrently and analysed independently before being merged during interpretation to ensure methodological triangulation and enhance validity.

Research Context and Timeframe

Data collection occurred between September 2022 and April 2023, a period characterized by rapid institutional experimentation with generative AI tools in both higher education and corporate learning environments. This timeframe reflects a stage where GenAI had moved beyond early adoption and into structured workplace integration, particularly in instructional design and learning development departments.

At the time of data collection, organizations varied widely in their AI governance maturity, ranging from unrestricted exploratory use to highly regulated environments with strict data privacy controls.

Population and Sampling Strategy

Target Population

The target population consisted of professionals involved in instructional design and learning development roles across educational, corporate, governmental, and nonprofit sectors. This included instructional designers, e-learning developers, learning experience designers (LXDs), training specialists, and instructional technologists engaged in the development of digital learning environments.

Sample Size and Composition

A total of 262 participants completed the quantitative survey in Saudi Arabia. From this pool, 12 participants were purposefully selected for qualitative focus group participation based on their experience level, sector diversity, and reported frequency of GenAI use.

Sampling Technique

A stratified purposive sampling strategy was employed to ensure representation across:

- Sector (higher education, corporate training, government, nonprofit)
- Experience level (early-career to senior professionals)
- Organizational AI maturity (low, moderate, advanced adoption environments)
- Frequency of GenAI use (occasional to intensive users)

Participants were recruited through professional instructional design networks, LinkedIn learning communities, educational technology associations, and corporate learning development forums.
This approach ensured that the dataset reflected both breadth of adoption patterns and depth of experiential insight.

Participant Demographics
Survey Participants (n = 262)

Category	**Distribution**
Instructional Designers	41%
Learning Experience Designers	22%
Corporate Trainers / L&D Specialists	19%
Instructional Technologists	10%
Academic Faculty (design roles)	8%

Sector Distribution

Sector	**Percentage**
Higher Education	46%
Corporate Training	32%
Government / Public Sector	12%
Nonprofit / NGOs	10%

Experience Level

Experience	**Percentage**
0–3 years	18%
4–7 years	34%
8–12 years	27%
13–20 years	15%
20+ years	6%

Focus Group Participants (n = 12)
Focus group participants were selected to reflect diversity in organizational context and AI exposure.

Attribute	**Range**
Age Range	27–54 years
Experience	2–18 years
Sectors Represented	Higher education (5), corporate (4), government (2), nonprofit (1)
AI Adoption Level	Early (3), intermediate (5), advanced (4)

Participants were distributed across multiple organizations with varying levels of AI governance maturity, allowing for comparative insight into institutional influences on adoption behaviour.

Data Collection Instruments

Survey Instrument

A structured online survey was developed specifically for this study due to the absence of a validated instrument targeting GenAI adoption in instructional design contexts.
The survey consisted of 22 items, organized into five sections:

1. Demographic information
2. AI usage frequency and patterns
3. Perceived usefulness and performance outcomes

4. UTAUT-based constructs
5. Open-ended reflection items

Items were mapped to modified UTAUT constructs:

- Performance Expectancy
- Effort Expectancy
- Facilitating Conditions
- Attitude toward AI use

A 5-point Likert scale was used for all attitudinal items, ranging from strongly negative to strongly positive responses.

Construct Items Examples

Construct	Example Item
Performance Expectancy	"GenAI tools improve the quality and efficiency of my instructional design outputs."
Effort Expectancy	"I find GenAI tools easy to integrate into my existing design workflow."
Facilitating Conditions	"My organization provides adequate support for using AI tools in instructional design."
Attitude	"I feel positively about using generative AI as part of my instructional design practice."

Open-ended questions captured qualitative insights regarding benefits, challenges, and ethical practices.

Focus Group Protocol

The qualitative phase used a semi-structured focus group protocol consisting of 7 guiding questions designed to explore:

- Workflow integration of GenAI
- Task-level usage patterns
- Perceived productivity and quality changes
- Organizational policies and constraints
- Ethical considerations and professional judgment
- Prompt engineering strategies
- Human–AI collaboration experiences

Sessions lasted approximately 75–90 minutes and were conducted via encrypted video conferencing platforms. All sessions were audio-recorded and transcribed verbatim.

Procedure

Phase 1: Pilot Testing

The survey instrument was pilot-tested with 18 instructional design professionals not included in the final dataset. Feedback focused on clarity of AI-related terminology, survey length, and interpretability of Likert-scale anchors. Minor revisions were made to improve item clarity and reduce redundancy.

Phase 2: Survey Administration

The finalized survey was distributed electronically using professional association mailing lists and instructional design communities. Participation was voluntary and anonymous. Consent was obtained at the beginning of the survey.

The survey remained open for 10 weeks, during which reminder notifications were sent biweekly to improve response rates.

Phase 3: Focus Group Implementation

From survey respondents who indicated willingness to participate in follow-up interviews, 12 individuals were purposively selected.

The focus group was conducted in three smaller sessions (4 participants per session) to encourage richer interaction and reduce response dominance effects. Each session followed the same protocol structure.

Data Analysis

Quantitative Analysis

Survey data were analysed using descriptive and inferential statistical techniques. Descriptive statistics (means, frequencies, standard deviations) were used to summarize adoption behaviours. Then, the cross-tabulation analysis examined relationships between AI usage frequency and professional role. Further, the correlation analysis explored relationships among UTAUT constructs. Finally, the regression modelling was applied to identify predictors of AI adoption intensity. All statistical analyses were conducted using SPSS (Version 29).

Qualitative Analysis

Focus group transcripts were analysed using thematic analysis following Braun and Clarke's (2006) six-phase framework:

1. Familiarization with data
2. Initial code generation
3. Theme identification
4. Theme review
5. Theme definition and naming
6. Interpretation and synthesis

An inductive coding approach was used, allowing themes to emerge from participant narratives rather than imposing predefined categories.
To enhance credibility, a dual-coding strategy was applied:

- Researcher 1 used NVivo software
- Researcher 2 conducted manual coding

Discrepancies were resolved through iterative discussion and consensus building.

Integration of Quantitative and Qualitative Data

A convergent triangulation strategy was used to integrate findings.
Three integration techniques were applied, firstly, the convergence comparison in which identifying overlapping findings across datasets was applied. Then, the complementary explanation (using qualitative data to explain quantitative trends). Then expansion analysis was applied for identifying insights present in one dataset but absent in the other. For example, statistical evidence of high adoption rates was contextualized through qualitative accounts describing workflow acceleration, while reported challenges were explained through narratives around prompt engineering difficulty and organizational constraints.

Ethical Considerations

The study adhered to institutional ethical guidelines for human subject research. Participation was voluntary, and informed consent was obtained from all participants. Data were anonymized prior to analysis to protect confidentiality.
Given the sensitivity of workplace AI usage policies, additional precautions were taken to remove identifiable organizational references from qualitative transcripts.

Methodological Rigor and Trustworthiness

Several strategies were employed to ensure rigor:

- Triangulation of quantitative and qualitative data
- Member checking of focus group summaries
- Dual coding of qualitative data
- Pilot testing of instruments
- Use of validated theoretical framework (UTAUT)

These measures enhanced the credibility, transferability, and dependability of findings.

RESULTS

Overview of Analysis

This section presents findings from the quantitative survey (n = 262) and qualitative focus groups (n = 12). Results are organized according to the four research questions and interpreted through the UTAUT framework. Quantitative findings are reported using descriptive and relational statistics, while qualitative findings are presented through thematic analysis. The integration of both datasets provides a comprehensive account of generative AI adoption in instructional design practice.

RQ1: Integration and Use of Generative AI in Instructional Design Workflows
Quantitative Findings: Adoption Patterns and Frequency of Use
Results indicate a high level of engagement with generative AI tools among instructional design professionals. A majority of respondents reported regular or frequent use of GenAI in their daily workflow.

Table 1 Frequency of Generative AI Use in Instructional Design Work

Usage Frequency	Percentage	n
Very frequent use	28%	73
Frequent use	34%	89
Occasional use	21%	55
Rare use	12%	31
Never use	5%	14

Overall, 62% of participants reported frequent or very frequent use, indicating that GenAI has moved beyond experimental use into routine professional practice for most respondents.

Integration Points in Instructional Design Workflow
Participants reported integrating GenAI at multiple stages of instructional design, with a clear preference for early-stage design activities.

Table 2 Stages of Instructional Design Where GenAI Is Used

Workflow Stage	Percentage
Early-stage planning (analysis & ideation)	46%
Content development phase	36%
Assessment design phase	12%
Final review and refinement	6%

Focus group data confirmed that AI is primarily used to accelerate ideation, structure course outlines, and generate first drafts rather than final instructional products.
One participant explained:
"It's almost always my starting point now. I use it to get ideas on structure and then refine everything afterward."

Task-Level Usage of Generative AI

Table 3 Instructional Design Tasks Supported by GenAI

Task Category	Percentage
Drafting learning objectives	69%
Creating assessments	61%
Developing course outlines	57%
Content summarization	52%
Instructional feedback generation	39%
Multimedia script writing	33%

These findings suggest that GenAI is most frequently used for structured and semi-structured tasks rather than high-stakes pedagogical decision-making.

Qualitative Theme: GenAI as an "Ideation Partner"
Three major themes emerged from qualitative data:

1. Rapid ideation acceleration
2. Workflow scaffolding
3. Draft-first design behaviour

Across all focus groups, participants consistently described GenAI as a tool that supports initial thinking rather than final instructional decisions.
One participant noted:
"It doesn't replace what I do it gets me to a workable draft in minutes instead of hours."

Construct Relationship: Performance Expectancy and Use Behaviour
Survey correlations revealed a strong positive relationship between perceived performance expectancy and frequency of use ($r = .71$, $p < .01$). Participants who reported higher perceived productivity gains were significantly more likely to integrate GenAI at earlier workflow stages.

RQ2: Perceived Benefits and Efficiency Gains
Quantitative Findings: Perceived Efficiency Improvement

Table 4 Perceived Efficiency Gains from GenAI Use

Efficiency Level	Percentage
Very significant improvement	19%
Significant improvement	31%
Moderate improvement	27%
Slight improvement	15%
No improvement	8%

Overall, 77% of respondents reported moderate to very significant efficiency gains, suggesting strong perceived performance value.

Key Perceived Benefits

Table 5 Most Frequently Reported Benefits

Benefit Category	Mentions
Faster content development	112
Reduced workload burden	94
Improved ideation quality	78
Increased productivity	73
Enhanced instructional creativity	61

Qualitative Theme: Efficiency Through Cognitive Offloading
Focus group participants consistently described GenAI as reducing cognitive load in early-stage design tasks. Rather than replacing expertise, AI was perceived as redistributing effort.
One participant stated:
"It takes away the blank page problem. I can react to something instead of starting from nothing."
Another noted:
"I'm not spending less time thinking I'm spending more time refining."

Construct Relationship: Effort Expectancy and Perceived Benefit
Correlation analysis showed that ease of use significantly predicted perceived efficiency gains ($r = .64$, $p < .01$). Participants who reported higher usability also reported stronger productivity improvements, suggesting that effort expectancy plays a critical mediating role in perceived value.

RQ3: Emerging Best Practices in GenAI Use
Quantitative Findings: Adoption of Best Practices

Table 6 Reported Professional Practices for Responsible GenAI Use

Practice	Percentage
Human verification of AI output	84%
Combining AI with professional expertise	79%
Transparency in AI use	63%
Ethical review of content	58%
Structured prompt engineering	52%
Institutional guideline compliance	44%

Qualitative Theme: Structured Human Oversight
Three dominant practice patterns emerged:
1. Verification-first workflows
Participants consistently emphasized reviewing AI outputs before instructional use.
"Nothing goes directly into a course without checking it line by line."
2. Transparent AI disclosure practices
Many designers reported disclosing AI use to stakeholders or subject matter experts.
"I always flag which sections were AI-assisted so reviewers know what to focus on."
3. Iterative prompt refinement
Participants described prompt engineering as an evolving skill rather than a fixed competency.
"The quality of output depends entirely on how much you refine the prompt."

Domain-Specific Practice Theme: Pedagogical Safeguarding
Instructional designers consistently emphasized the need to protect pedagogical integrity.
AI-generated content was frequently described as:

- Structurally useful but pedagogically incomplete
- Efficient but lacking instructional nuance
- Helpful for drafting but not decision-making

Construct Relationship: Facilitating Conditions and Practice Development
Organizations with stronger AI governance structures showed significantly higher adoption of structured best practices ($\beta = .58$, $p < .01$). Conversely, weak institutional support resulted in individualized and informal AI use strategies.

RQ4: Challenges and Barriers in GenAI Integration
Quantitative Findings: Primary Challenges

Table 7 Reported Barriers to Effective GenAI Use

Challenge	Frequency
Verifying accuracy of outputs	96
Prompt engineering difficulty	81
Lack of pedagogical alignment	64
Organizational restrictions	59
Data privacy concerns	53
Limited customization	47

Qualitative Theme: Reliability and Trust Deficit
A dominant concern across all groups was the reliability of AI-generated outputs.
Participants frequently described the need for constant verification:
"You cannot assume it's correct. You have to double-check everything."
Another participant described the system as:
"Fast, but not always right so you still end up doing the heavy lifting."

Challenge Theme: Prompt Engineering as Cognitive Load
Many participants reported that prompt development often required more effort than traditional design methods, particularly for complex instructional tasks.
"Sometimes I spend longer writing the prompt than just writing the content myself."
This created a paradox in effort expectancy, where perceived ease of use varied significantly by task complexity.

Organizational Barrier Theme: Policy Constraints and Workarounds
Participants in restricted environments reported using informal strategies to bypass organizational limitations, including:

- Avoiding sensitive terminology in prompts
- Using personal devices for experimentation
- Restricting AI use to non-confidential tasks

"We have to be careful with what we input, so it limits what we can actually do."

Construct Relationship: Compounding Barriers
Regression analysis indicated that organizational constraints amplified perceived effort ($\beta = .49$, $p < .01$), reducing overall adoption intensity even among high-performance expectancy users.

Integrated Summary of Findings
Across all research questions, three overarching patterns emerged:

- GenAI is primarily an early-stage design accelerator

It is most frequently used for ideation, drafting, and structuring rather than final instructional decision-making.

- Adoption is driven by perceived productivity gains but moderated by trust

Performance expectancy is high, but trust deficits limit full integration.

- Organizational conditions significantly shape practice variability

Institutional policies and support structures strongly influence both adoption depth and sophistication.

The findings demonstrate that generative AI is not simply a productivity tool in instructional design but a reconfiguration of professional practice involving new forms of human–AI collaboration, distributed cognitive work, and organizationally mediated adoption pathways.

DISCUSSION

Overview of Key Contributions

This study set out to examine how instructional designers engage with generative artificial intelligence within their professional workflows, using an expanded UTAUT lens combined with a human–AI collaboration perspective. Across the integrated quantitative and qualitative findings, three broad contributions emerge.
First, the study clarifies that generative AI adoption in instructional design is not merely a matter of technology acceptance but a workflow reconfiguration process, where designers redistribute cognitive and procedural labour between themselves and AI systems.
Second, it demonstrates that the classic UTAUT constructs remain relevant but require reinterpretation in AI-augmented environments, where "use behaviour" is no longer a simple adoption outcome but an evolving interaction pattern.
Third, the findings extend human–AI collaboration theory by showing that instructional designers do not treat AI as either a tool or a partner in a fixed sense; instead, they dynamically shift between roles such as supervisor, editor, co-designer, and validator depending on task complexity, risk level, and institutional constraints.

These contributions collectively reposition GenAI adoption from a linear acceptance model to a negotiated socio-technical practice embedded in instructional design ecosystems.

Reinterpreting UTAUT in Generative AI Environments

Performance Expectancy as "Augmented Productivity Logic"

Performance Expectancy remains the most dominant explanatory construct in this study, consistent with UTAUT tradition (Venkatesh et al., 2003; Dwivedi et al., 2019). However, its meaning is substantively transformed in the context of generative AI.

Rather than simply reflecting "improved job performance," performance expectancy in this study reflects a form of augmented productivity logic, where instructional designers perceive AI as a mechanism to expand output capacity, compress production timelines, and multiply ideation possibilities.

Importantly, this expectation is not uniform across tasks. Designers consistently reported higher perceived value in structured activities (e.g., drafting objectives, creating assessment items) compared to open-ended pedagogical design. This suggests that performance expectancy is task-contingent rather than global, a nuance not fully captured in traditional UTAUT formulations.

This finding aligns with emerging research suggesting that GenAI adoption is driven by perceived "micro-efficiencies" rather than holistic productivity gains (Luo et al., 2024).

Effort Expectancy as a Skill-Dependent Variable

A major theoretical extension emerging from this study is the reconceptualization of Effort Expectancy. In classical UTAUT, effort expectancy refers to perceived ease of system use. In GenAI-mediated environments, however, this construct becomes user-competence dependent rather than interface-dependent.

The data suggest a paradox: generative AI reduces effort in output generation but increases effort in input formulation, particularly through prompt engineering. As designers become more experienced, effort expectancy shifts from a barrier to a facilitative mechanism.

This creates a nonlinear adoption curve where initial engagement is effort-heavy, followed by increasing efficiency as tacit prompting expertise develops. Thus, effort expectancy should be reframed as a dynamic learning trajectory rather than a static perception.

This reinterpretation extends Santana's (2024) argument that prompting is not a technical skill alone but a form of epistemic negotiation between human intention and machine interpretation.

Facilitating Conditions as Institutional Algorithmic Governance

Facilitating Conditions traditionally capture infrastructure and organizational support. In this study, however, they function as a form of algorithmic governance layer that shapes not only access to technology but also the epistemic boundaries of its use.

Institutional restrictions on data input, licensing constraints, and ethical policies were found to directly influence not only whether AI was used but *how* it was used. Participants frequently described workaround strategies, indicating that facilitating conditions do not simply enable or constrain adoption they actively shape shadow innovation practices.

This extends prior work of Yalçın, Ursavaş and Klein (2021) suggesting that governance structures are not neutral enablers but active co-producers of technology behavior. In restrictive environments, adoption does not decline; instead, it becomes redistributed into informal and partially concealed workflows.

Attitude as a Stability Mechanism in High-Uncertainty Environments

Attitude in this study operates less as a predictor of adoption and more as a stabilizing mechanism under uncertainty. Instructional designers expressed what can be described as "guarded trust," where enthusiasm for efficiency gains coexists with persistent scepticism about output reliability.

This duality is crucial. Unlike earlier technologies where attitudes become more positive with increased familiarity, attitudes toward GenAI remain structurally ambivalent. This is due to the probabilistic and non-deterministic nature of model outputs.

As a result, attitude functions as a regulatory checkpoint, ensuring that human verification remains embedded in workflows even under high performance expectancy conditions.

Extending Human–AI Collaboration Theory

From Tool Use to Role Fluidity

A central theoretical contribution of this study is the identification of role fluidity in human–AI collaboration. Existing models often position AI as either a tool (instrumental view) or a partner (collaborative view). However, findings from instructional designers indicate that these roles are not fixed.
Instead, designers shift between multiple relational positions:

- AI as generator during ideation phases
- AI as accelerator during drafting phases
- AI as editor surrogate during refinement phases
- AI as questionable authority during evaluation phases

This role-switching behaviour suggests that human–AI collaboration is best understood as a context-sensitive orchestration process rather than a stable partnership structure.

Emergence of "Supervisory Collaboration"

The data also support the emergence of what can be termed supervisory collaboration, where humans retain ultimate epistemic authority while actively integrating AI-generated outputs into production workflows.
Unlike classical human-in-the-loop systems that emphasize correction, supervisory collaboration involves continuous co-production with embedded verification cycles. Instructional designers do not simply correct AI outputs; they iteratively reshape them while simultaneously redefining task boundaries.
This aligns with Sterz et al. (2024), but extends their notion of oversight by showing that supervision is not episodic it is continuous and embedded within every stage of instructional production.

Cognitive Redistribution in Instructional Design Workflows

A further theoretical insight is the redistribution of cognitive labour. GenAI does not eliminate cognitive work; it redistributes it across different phases of design.

- Ideation shifts from generation → selection
- Drafting shifts from writing → refining
- Evaluation shifts from production → verification
- Structuring shifts from planning → orchestration

This redistribution suggests that GenAI transforms instructional design into a meta-cognitive discipline, where the primary skill is no longer content creation but judgment calibration.

Integration with Existing Literature

The findings both reinforce and extend prior scholarship in three key ways.
First, consistent with Weng and Chiu (2023), GenAI enhances efficiency and supports personalized learning design. However, this study adds that efficiency gains are uneven and depend heavily on task structure and user expertise.
Second, aligning with Luo et al. (2024), instructional designers use GenAI for ideation and routine tasks. Yet, this study extends their findings by showing that usage is embedded within organizational constraint systems, which significantly shape adoption pathways.
Third, echoing Ivens (2023) GenAI is reshaping educational content creation. However, this study demonstrates that the transformation is not purely technological but institutionally negotiated, mediated through policies, ethical norms, and informal practices.

A Revised Conceptual Model of GenAI Adoption in Instructional Design

Based on the findings, a revised conceptualization of UTAUT in GenAI contexts is proposed.
Rather than a linear model predicting "use behaviour," adoption should be understood as a recursive interaction system involving:

1. Task-level performance expectancy (micro-efficiency expectations)
2. Skill-mediated effort expectancy (prompt literacy development)
3. Institutional facilitation structures (governance and constraints)
4. Attitudinal stabilization under uncertainty
5. Continuous role negotiation in human–AI interaction cycles

This model positions GenAI adoption as an evolving loop rather than a one-time acceptance decision.

CONCLUSION AND PRACTICAL IMPLICATIONS

Overall, this study demonstrates that generative AI adoption in instructional design cannot be adequately explained through traditional technology acceptance frameworks alone. While UTAUT provides a strong structural foundation, its constructs require reinterpretation to account for dynamic interaction, skill development, and institutional governance.

More importantly, the study shows that instructional designers are not passive adopters of AI systems. They are active agents in constructing hybrid human–AI workflows that continuously evolve through practice, constraint, and reflection.

In this sense, generative AI does not simply enter instructional design it becomes embedded within its cognitive and organizational architecture, fundamentally reshaping how instructional knowledge is produced, validated, and enacted.

From a theoretical standpoint, the implications of this study extend beyond instructional design practice where it shared that organizations should not only provide access but recognize that governance structures actively shape innovation pathways. Then, training should focus less on tool usage and more on prompt epistemology and evaluative reasoning. Further, the instructional design theory should integrate AI as a co-constitutive element of design cognition rather than an external support system. These implications suggest that GenAI is not simply a new tool in instructional design it is a restructuring force for the discipline itself.

Limitations

The study's theoretical claims should be interpreted within several boundary conditions.
First, the dynamic nature of GenAI systems means that adoption behaviours may shift rapidly as models evolve.
Second, the reliance on self-reported data introduces interpretive limitations regarding actual behavioural patterns.
Third, institutional variability across sectors suggests that facilitating conditions may operate differently in high-regulation versus low-regulation environments.
These constraints indicate that the proposed conceptual model should be treated as provisional and context-sensitive rather than universally generalizable.

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