Extending Henschke's MIPI: An AI-supported framework for instrument design in doctoral research across disciplines

John A. Henschke, University of Missouri & Lindenwood University, USA

Abstract

Doctoral students frequently face challenges in designing valid and reliable research instruments, often due to limited structured frameworks, inconsistent methodological guidance, and time constraints. This article addresses these issues by extending Henschke's Modified Instructional Perspectives Inventory (MIPI) into an AI-Supported Instrument Design (AI-SID) framework. Grounded in andragogical theory (Knowles, 1972; Henschke, 2008, 2017, 2020, 2021), the proposed model integrates human-centered theoretical constructs—beliefs, feelings, and behaviors—with AI-assisted processes to enhance item generation, refinement, validation, and cross-disciplinary adaptation. The framework outlines a five-stage process that combines conceptual grounding, human–AI co-design, AI-assisted validation, iterative pilot testing, and contextual scalability. By positioning artificial intelligence as a complementary tool rather than a replacement for scholarly judgment, AI-SID promotes increased rigor, efficiency, and accessibility in doctoral research. The article contributes a practical, scalable model aligned with emerging trends in AI integration in higher education and calls for future empirical validation across disciplines.

Keywords: MIPI, AI-supported instrument design, doctoral research, andragogy, scale development, research methodology, higher education

Introduction

The design and development of valid and reliable research instruments remains a persistent challenge for doctoral students across disciplines. Despite extensive methodological training, many doctoral researchers struggle to translate abstract theoretical constructs into well-aligned survey items, interview protocols, or observational tools. Instrument development requires a sophisticated integration of theory, construct operationalization, and validation procedures—skills that are often unevenly developed and highly dependent on advisor expertise and disciplinary conventions (Creswell & Creswell, 2018; DeVellis & Thorpe, 2022). As a result, doctoral research frequently exhibits weaknesses in construct clarity, item alignment, and validation rigor, ultimately affecting the quality and credibility of findings.

A central issue underlying these challenges is the lack of structured, scalable frameworks for instrument design that can be applied across disciplines. While established models exist within specific fields, such as education, psychology, and the health sciences, these approaches are often siloed and not easily transferable to interdisciplinary or emerging research contexts (Boateng et al., 2018). Doctoral students frequently rely on adapting existing instruments or constructing new ones with limited guidance, leading to inconsistencies in methodological quality. Moreover, the process of instrument development is time-intensive and iterative, requiring multiple cycles of refinement, pilot testing, and validation that may not be feasible within the constraints of doctoral timelines (Furr, 2021).

Within the field of adult education, Henschke's Instructor Perspectives Inventory (IPI) and its subsequent adaptations, including the Modified Instructional Perspectives Inventory (MIPI), provide a notable example of a theoretically grounded and empirically validated instrument development framework (Knowles, 1972; Henschke, 2008, 2017, 2020, 2021). Rooted in andragogical theory, the MIPI emphasizes the alignment of beliefs, feelings, and behaviors in educational practice, with particular attention to constructs such as teacher empathy, learner-centered processes, and trust of learners . Importantly, the IPI/MIPI framework has demonstrated scalability and adaptability, having been utilized in 34 doctoral dissertations across diverse contexts. This body of work underscores the potential for a structured, theory-driven approach to instrument design that maintains both conceptual integrity and practical applicability.

At the same time, the rapid advancement of artificial intelligence (AI) technologies presents new opportunities to address longstanding challenges in research design. AI tools are increasingly being used to support literature synthesis, data analysis, and writing processes; however, their application in instrument development remains under-theorized and underdeveloped (Zawacki-Richter et al., 2019; Tlili et al., 2023). Existing studies suggest that AI can assist with tasks such as generating survey items, identifying redundancies, and improving clarity, yet there is limited integration of these capabilities within established methodological frameworks (Kasneci et al., 2023). Without a clear conceptual model, the use of AI in instrument design risks becoming ad hoc, inconsistent, and disconnected from theoretical foundations.

This gap highlights the need for a model that integrates the strengths of established frameworks, such as Henschke's MIPI, with the emerging capabilities of AI. Such an approach would enable doctoral students to engage in a more systematic, efficient, and rigorous process of instrument development while maintaining alignment with theoretical constructs. By positioning AI as a complementary tool rather than a replacement for human judgment, it is possible to enhance both the quality and scalability of instrument design across disciplines.

The purpose of this article is twofold. First, it seeks to extend Henschke's MIPI framework by situating it within a broader, cross-disciplinary context of doctoral research. Second, it proposes an AI-supported model for instrument design that integrates human theoretical grounding with AI-assisted development and validation processes. This model aims to provide doctoral students with a structured, replicable approach to instrument construction that addresses common methodological challenges while leveraging contemporary technological advancements.

To guide this inquiry, the following research questions are proposed:

1. How can Henschke's MIPI framework be extended to support instrument design across multiple academic disciplines in doctoral research?
2. In what ways can artificial intelligence be integrated into the instrument development process to enhance validity, reliability, and efficiency?
3. What are the implications of an AI-supported instrument design model for doctoral research training and methodological practice?

By addressing these questions, this article contributes to the growing intersection of AI and research methodology, offering a theoretically grounded and practically applicable framework for improving instrument design in doctoral education.

Theoretical and Empirical Foundation

The development of valid and theoretically grounded research instruments in adult education has been significantly shaped by the work of John A. Henschke, particularly through the evolution of the Instructor Perspectives Inventory (IPI) and its subsequent adaptations. The IPI emerged from Henschke's sustained inquiry into the fundamental question: what beliefs, feelings, and behaviors are essential for effective adult educators. This question aligns closely with the broader andragogical tradition, which emphasizes the holistic integration of cognitive, affective, and behavioral dimensions of teaching and learning (Knowles et al., 2020).

Henschke's original IPI was designed as a diagnostic and reflective tool to assess instructional orientations among adult educators. Through iterative empirical testing and factor analysis, the instrument identified seven core factors that characterize effective adult learning facilitation. These factors reflect a synthesis of theoretical constructs grounded in andragogy and validated through practice-based research. Over time, the IPI evolved into the Modified Instructional Perspectives Inventory (MIPI), which improved measurement precision and expanded applicability across contexts, including higher education, workforce training, and organizational leadership settings .

At the core of the IPI/MIPI framework (Knowles, 1972; Henschke, 2008, 2017, 2020, 2021) is the integration of **beliefs, feelings, and behaviors** as foundational constructs. This triadic structure reflects a key assumption of andragogy: that effective adult education is not merely a function of instructional technique, but rather the alignment between what educators believe, how they feel about learners, and how they act in practice (Merriam & Bierema, 2014). Beliefs guide pedagogical philosophy, feelings shape relational dynamics, and behaviors operationalize both in the learning environment. This alignment is essential for fostering authentic, learner-centered educational experiences.

Among the seven factors identified in the IPI/MIPI framework, **teacher trust of learners** consistently emerges as the most significant and influential construct. Empirical findings indicate that trust is not only central to the educator–learner relationship but also predictive of broader instructional effectiveness. Trust manifests in behaviors such as valuing learner autonomy, encouraging self-direction, and recognizing the experiential knowledge that adult learners bring to the educational setting . This emphasis aligns with contemporary research in adult learning, which highlights psychological safety and relational trust as critical conditions for deep learning and engagement (Dirkx, 2023).

The robustness and scalability of the IPI/MIPI framework are further demonstrated through its extensive use in doctoral research. To date, **34 doctoral dissertations have employed the IPI/MIPI model**, applying it across diverse disciplines including education, nursing, leadership studies, and organizational development. This widespread adoption underscores the instrument's versatility and empirical credibility. It also reflects the adaptability of its constructs, which are not limited to traditional classroom settings but extend to various adult learning environments. Such cross-contextual applicability is a hallmark of strong instrument design, indicating both conceptual clarity and practical relevance (Boateng et al., 2018).

The evolution of the IPI into the MIPI and related adaptations illustrates a continuous process of refinement and contextualization. One notable modification is the **MIPI-S (Modified Instructional Perspectives Inventory for Students)**, which shifts the perspective from educator self-assessment to learner perception. This adaptation enables researchers to examine congruency between instructor intent and student experience, thereby strengthening the validity of findings. Additionally, workplace adaptations have recontextualized the instrument for organizational settings, replacing “teacher” with “supervisor” and “learner” with “employee,” while preserving the underlying constructs. These modifications demonstrate the flexibility of the framework and its capacity to maintain theoretical integrity across domains .

A defining feature of Henschke’s work is the emphasis on **theory–practice congruency**. Drawing from the broader andragogical tradition, this principle asserts that effective educators must embody the principles they espouse. In other words, there should be alignment between theoretical commitments and observable behaviors in practice. This concept echoes Knowles’s assertion that adult education is not only a set of methods but also a philosophy that must be enacted authentically (Knowles et al., 2020). The IPI/MIPI framework operationalizes this idea by providing measurable indicators of congruency, allowing researchers to assess whether educators’ practices reflect their stated beliefs.

The importance of theory–practice congruency extends beyond individual educators to the broader field of research methodology. Instruments that are grounded in theory but disconnected from practice risk lacking ecological validity, while those based solely on practice may lack conceptual rigor. The IPI/MIPI model bridges this gap by integrating both dimensions, offering a balanced approach that is particularly valuable for doctoral researchers. As doctoral education increasingly emphasizes applied and interdisciplinary research, frameworks that support such integration are essential (Biesta, 2022).

To illustrate the foundational structure of the MIPI, Table 1 presents the core factors derived from Henschke’s work.

Table 1

Core Factors of Henschke’s IPI/MIPI Framework

MIPI Factors Table

Factor No.	Factor Name	Description
1	Planning and Delivery of Instruction	Structured and intentional organization of learning experiences

2	Learner-Centered Learning Processes	Emphasis on experiential, participatory, and self-directed learning
3	Teacher-Centered Learning Processes	Use of directive or instructor-led approaches when appropriate
4	Teacher Empathy with Learners	Sensitivity to learner needs, perspectives, and emotional states
5	Teacher Insensitivity Toward Learners	Lack of responsiveness to learner needs (reverse-scored construct)
6	Accommodating Learner Uniqueness	Recognition of individual differences and adaptive instructional strategies
7	Teacher Trust of Learners	Confidence in learners' abilities, autonomy, and self-direction

In summary, the IPI/MIPI framework represents a significant contribution to the field of adult education and research methodology. Its theoretical grounding in andragogy, combined with extensive empirical validation and adaptability, makes it a powerful tool for instrument design. The emphasis on beliefs, feelings, and behaviors, along with the central role of trust and the principle of theory–practice congruency, provides a comprehensive foundation for extending this framework into new domains, including AI-supported research design.

Problem in Current Doctoral Instrument Design

The design and development of research instruments in doctoral education continues to present significant methodological challenges across disciplines. Despite advances in research training and access to methodological resources, doctoral students frequently encounter persistent difficulties in constructing instruments that demonstrate conceptual clarity, validity, and reliability. These challenges are not isolated but reflect broader systemic issues in how research design is taught, supported, and operationalized within doctoral programs (Bair & Madera, 2019; Krumsvik, 2020).

A primary concern is the **lack of structured, cross-disciplinary frameworks** for instrument design. While individual disciplines such as psychology, education, and public health have established guidelines for scale development, these frameworks are often discipline-specific and not easily transferable (Clark & Watson, 2019). Doctoral students working in interdisciplinary or emerging fields are particularly disadvantaged, as they must navigate multiple methodological traditions without a unified model. This fragmentation results in inconsistent practices and varying levels of rigor in instrument development. Moreover, existing frameworks tend to emphasize statistical validation procedures while providing limited guidance on the earlier stages of construct conceptualization and item generation (Slavec & Drnovšek, 2012).

Closely related to this issue is the **over-reliance on dissertation advisors or previously developed instruments**. Doctoral students often depend heavily on their advisors for guidance in instrument design, which can lead to variability in quality depending on the advisor's methodological expertise. In many cases, students are encouraged to adopt or adapt existing instruments without fully understanding their theoretical foundations or contextual limitations (Shavelson, 2016). While using established instruments can be appropriate, uncritical adoption may result in misalignment between the instrument and the specific research context. This practice can compromise construct validity and limit the originality of doctoral research. Furthermore, reliance on borrowed instruments may discourage the development of methodological competence among doctoral students, reinforcing dependency rather than fostering independent research skills (Pyhältö et al., 2015).

Another critical issue is the **weak alignment between theoretical constructs and instrument items**. Effective instrument design requires a clear operationalization of constructs, ensuring that each item accurately reflects the underlying theoretical concept. However, doctoral students often struggle to bridge the gap between abstract theory and measurable indicators. This misalignment can lead to ambiguous or redundant items, reducing the overall validity of the instrument (MacKenzie et al., 2011). Inadequate construct definition is frequently cited as a major source of measurement error, particularly in social science research where constructs are complex and multifaceted. Without a systematic approach to aligning theory and measurement, instruments risk capturing superficial or unrelated dimensions of the phenomenon under study.

In addition, doctoral research often exhibits **limited and inconsistent validation strategies**. While methodological literature emphasizes the importance of multiple forms of validity—such as content, construct, and criterion validity—doctoral studies frequently rely on minimal validation procedures, often restricted to face validity or small pilot samples (Worthington & Whittaker, 2006). Time constraints, limited access to large samples, and lack of statistical expertise contribute to this issue. As a result, many doctoral instruments do not undergo rigorous validation processes, raising concerns about the reliability and generalizability of findings. Recent scholarship has highlighted the need for more robust and transparent validation practices, particularly in applied and interdisciplinary research contexts (Flake et al., 2017).

The **time-intensive and iterative nature of instrument development** further complicates the process for doctoral students. Developing a high-quality instrument typically involves multiple stages, including literature review, item generation, expert review, pilot testing, and statistical analysis. Each stage requires careful planning and execution, often extending beyond the practical timelines of doctoral programs (Ruel et al., 2016). Consequently, students may rush the process or omit critical steps, leading to instruments that are underdeveloped or insufficiently tested. This challenge is exacerbated by the absence of scalable tools or models that can streamline the process without sacrificing rigor.

Recent developments in research methodology have begun to address some of these challenges, particularly through the integration of digital tools and analytics. However, the application of emerging technologies, including artificial intelligence (AI), in instrument design remains limited and under-theorized. While AI has demonstrated potential in areas such as natural language processing and data analysis, its role in supporting construct development, item generation, and validation has not been systematically explored within doctoral research training (Bond et al., 2023). Without a clear framework for integrating these tools, their use remains inconsistent and largely dependent on individual initiative.

Taken together, these issues point to a critical gap in doctoral education: the need for a structured, scalable, and theoretically grounded approach to instrument design that can be applied across disciplines. Addressing this gap requires not only improved methodological training but also the development of frameworks that integrate theoretical rigor with practical efficiency. Such frameworks must support doctoral students in navigating the complexities of construct development, item alignment, and validation while accommodating the constraints of time and resources inherent in doctoral research.

Conceptual Framework: AI-Supported Instrument Design (AI-SID)

The increasing complexity of doctoral research, coupled with the rapid advancement of artificial intelligence (AI), necessitates a rethinking of traditional approaches to instrument design. This study introduces the **AI-Supported Instrument Design (AI-SID)** framework as an extension—not a replacement—of Henschke's Modified Instructional Perspectives Inventory (MIPI). While MIPI provides a robust theoretical foundation grounded in andragogy, it does not explicitly address how emerging technologies can enhance the instrument development process. The AI-SID framework bridges this gap by integrating **human theoretical grounding with AI-assisted development**, creating a hybrid model that enhances rigor, efficiency, and scalability.

The core principle of AI-SID is that **theory must remain human-centered**, while AI functions as a methodological support tool. This aligns with contemporary perspectives in educational technology, which emphasize augmentation rather than automation of human cognition (Luckin et al., 2022). In this framework, AI does not replace the researcher's role in conceptualization or interpretation; rather, it supports iterative refinement, pattern recognition, and analytical efficiency. By embedding AI within a structured, theory-driven process, the AI-SID model ensures that technological assistance enhances, rather than undermines, methodological integrity.

The AI-SID Model: A Five-Stage Framework

Stage 1: Conceptual Grounding

The first stage of the AI-SID model emphasizes the identification and clarification of constructs using established theoretical frameworks, such as MIPI. This stage is critical because poorly defined constructs are a primary source of measurement error in research (Colquitt et al., 2019).

Doctoral students begin by aligning their research questions with clearly articulated constructs, ensuring conceptual coherence before any item generation occurs.

Frameworks like MIPI provide predefined factors—such as trust, empathy, and learner-centeredness—that can serve as anchors for construct development. Grounding instrument design in theory enhances both content and construct validity, ensuring that items reflect meaningful dimensions of the phenomenon under study. AI tools may assist in summarizing literature or mapping conceptual relationships; however, the responsibility for defining constructs remains with the researcher. This stage reinforces the importance of theoretical literacy as the foundation of rigorous instrument design (Tight, 2020).

Stage 2: Human–AI Co-Design

In the second stage, AI is introduced as a collaborative tool for generating initial survey or interview items. Large language models (LLMs), such as generative AI systems, can produce diverse item pools based on specified constructs, reducing the cognitive burden on researchers and accelerating early-stage development (Dwivedi et al., 2023). For example, AI can generate multiple variations of items related to "trust of learners," allowing researchers to select and refine those most appropriate for their context.

However, this process is inherently iterative and requires human oversight. Researchers must evaluate AI-generated items for clarity, tone, cultural sensitivity, and disciplinary relevance. This stage reflects a co-design approach in which human judgment guides the selection and refinement of AI outputs. Studies have shown that combining human expertise with AI-generated content results in higher-quality outputs than either approach alone (Zhai et al., 2024). Thus, AI-SID positions the researcher as the primary decision-maker, with AI serving as an ideation and drafting tool.

Stage 3: AI-Assisted Validation

The third stage introduces AI as a tool for preliminary validation. AI systems can analyze item sets to identify issues such as redundancy, ambiguity, and misalignment with constructs. For instance, natural language processing (NLP) techniques can detect semantic overlap between items, helping to reduce redundancy and improve scale efficiency (Miner et al., 2020). Additionally, AI can assess readability and linguistic clarity, ensuring that items are accessible to the target population.

Importantly, AI-assisted validation supports **early-stage content validity**, which is often underdeveloped in doctoral research. By providing rapid feedback on item quality, AI enables researchers to refine instruments before engaging in more resource-intensive validation procedures. While AI cannot replace expert review or statistical validation, it enhances the efficiency and depth of initial evaluation. This aligns with recent calls for more transparent and iterative validation processes in social science research (Flake & Fried, 2020).

Stage 4: Pilot Testing and Iteration

The fourth stage combines traditional pilot testing with AI-supported feedback analysis. Pilot studies remain essential for assessing reliability, factor structure, and overall instrument performance. However, AI can augment this process by analyzing qualitative feedback, identifying response patterns, and suggesting areas for refinement. For example, machine learning algorithms can cluster open-ended responses to highlight common issues or themes, providing deeper insight into participant experiences (Chen et al., 2022).

This stage reflects a cyclical process of testing and refinement, where both human interpretation and AI analytics contribute to instrument improvement. By integrating AI into pilot analysis, researchers can process larger datasets more efficiently and identify subtle patterns that may be overlooked through manual analysis alone. This hybrid approach enhances both the rigor and scalability of instrument development, particularly in time-constrained doctoral research contexts.

Stage 5: Cross-Disciplinary Adaptation

The final stage of the AI-SID model focuses on the transferability of instruments across disciplines. One of the key limitations of traditional instrument design is its context-specific nature, which restricts broader applicability. AI-SID addresses this challenge by leveraging AI's capacity to adapt language and contextual references while preserving underlying constructs.

For example, a construct such as "trust of learners" can be reframed as "trust of employees" in business contexts or "trust of patients" in healthcare settings. AI can assist in generating context-specific item variations that maintain conceptual integrity while enhancing relevance. This capability supports the development of instruments that are both theoretically consistent and contextually adaptable, a critical requirement in interdisciplinary research (Holmes et al., 2022).

The ability to extend instruments across fields such as education, nursing, business, and leadership studies demonstrates the scalability of the AI-SID framework. By maintaining a stable theoretical core while allowing flexible adaptation, the model aligns with contemporary demands for interdisciplinary research and innovation.

Conclusion of Framework

The AI-SID framework represents a significant advancement in instrument design methodology by integrating human-centered theory with AI-supported processes. Each stage of the model reinforces the importance of theoretical grounding while leveraging AI to enhance efficiency, clarity, and scalability. By extending the MIPI framework into an AI-supported context, this model provides doctoral students with a structured, replicable approach to instrument development that addresses longstanding challenges in research design.

Application Example: Extending MIPI with an AI Component

The Modified Instructional Perspectives Inventory (MIPI) represents one of the most sustained and adaptable frameworks for examining instructional beliefs, feelings, and behaviors in adult education. Originally developed from Henschke's Instructor Perspectives Inventory (IPI), the MIPI emerged through an iterative process involving factor analysis, instrument refinement, and application across multiple educational contexts. The framework was grounded in andragogical theory and emphasized the congruency between educational philosophy and instructional practice. Over time, the instrument was modified for use with students (MIPI-S), workplace leadership settings, and interdisciplinary doctoral research contexts. The use of the IPI/MIPI framework in 34 doctoral dissertations demonstrates its scalability, empirical utility, and theoretical durability.

The original development of MIPI followed a traditional instrument design process involving item generation, pilot testing, exploratory factor analysis, and validation procedures. Initial items were constructed around major dimensions of adult learning facilitation, including teacher empathy, learner-centered processes, and teacher trust of learners. Subsequent analyses refined these constructs into measurable factors that could be used across educational settings. This approach reflected best practices in scale development at the time, emphasizing construct validity and internal consistency (DeVellis & Thorpe, 2022). However, the original process was highly labor-intensive and dependent on extensive human analysis. Contemporary advances in artificial intelligence (AI) provide opportunities to enhance each stage of this process while maintaining the human-centered andragogical foundation of MIPI.

The first area where AI can extend MIPI is **item generation**. Traditionally, researchers manually generated item pools based on theoretical constructs and literature reviews. While effective, this process was time-consuming and limited by the researcher's individual perspective. Generative AI tools can now support this stage by rapidly producing diverse item variations aligned with specified constructs. For example, researchers seeking to operationalize "teacher trust of learners" can prompt AI systems to generate survey items reflecting learner autonomy, empathy, or collaborative engagement. Recent research demonstrates that AI-supported item generation can increase efficiency while maintaining conceptual relevance when guided by human oversight (Ranieri et al., 2025). AI also enables researchers to explore alternative wording, readability levels, and contextual framing across disciplines, thereby expanding the richness of initial item pools.

Despite these advantages, AI-generated items require substantial human refinement. Within the extended MIPI framework, researchers remain responsible for ensuring theoretical congruency, cultural appropriateness, and disciplinary relevance. This human–AI co-design process aligns with emerging scholarship emphasizing that AI should augment, rather than replace, scholarly judgment in educational research (Dwivedi et al., 2023). For instance, an AI-generated item such as "My instructor believes students can independently solve learning challenges" may be refined by researchers to better reflect the nuanced construct of andragogical trust embedded within MIPI. Thus, AI serves as an ideation partner, while human expertise preserves theoretical integrity.

The second area of enhancement involves **factor refinement**. In the original MIPI development, factor analysis required multiple cycles of statistical testing and interpretation. AI-assisted analytics now allow researchers to identify semantic overlap, redundancy, and latent conceptual relationships before large-scale statistical analysis begins. Natural language processing (NLP) techniques can cluster similar items, identify ambiguous wording, and detect inconsistencies in construct representation (Miner et al., 2020). These capabilities are particularly useful during early-stage refinement, where doctoral researchers often struggle with excessive or repetitive items.

For example, within the "Teacher Trust of Learners" factor, AI systems can identify whether multiple items measure the same dimension of trust, such as autonomy or respect, and recommend consolidation. AI can also suggest missing dimensions within the construct. If current items emphasize learner independence but neglect emotional support, AI analysis may recommend generating additional items related to empathy and encouragement. This process strengthens content coverage while reducing redundancy, improving both scale efficiency and conceptual coherence.

A third major enhancement concerns **validation processes**. Traditional instrument validation relies heavily on expert review, pilot testing, and statistical procedures such as confirmatory factor analysis (CFA). While these remain essential, AI can support preliminary validation by evaluating item clarity, readability, and construct alignment before formal testing occurs. Recent studies in AI-assisted instrument development have demonstrated the utility of AI in identifying problematic items and supporting content validity assessments (Guo et al., 2024; Capinding, 2024). AI systems can rapidly analyze whether items align semantically with intended constructs, thereby reducing the likelihood of construct contamination.

Within the extended MIPI framework, AI-assisted validation complements—not replaces—traditional psychometric testing. Human experts continue to determine theoretical appropriateness, while AI accelerates preliminary screening and revision. This hybrid process is particularly beneficial for doctoral students, who often face constraints related to time, sample access, and methodological expertise. AI-supported validation allows researchers to enter pilot testing phases with more refined instruments, increasing the efficiency of subsequent empirical analyses.

An illustrative example of this process can be seen through the extension of the **Teacher Trust of Learners** construct. Originally, this factor emphasized educator confidence in learner autonomy, self-direction, and dignity. Using AI-supported development, researchers can expand this construct by generating context-specific items for disciplines such as nursing, leadership, or business education. For example, AI may generate nursing-focused items emphasizing clinical decision-making autonomy or leadership-focused items addressing employee empowerment. Researchers can then refine these items to ensure alignment with the original andragogical meaning of trust.

Additionally, AI can support multilingual and cross-cultural adaptations of the MIPI framework. By generating equivalent item structures across languages and contexts, AI facilitates broader scalability while preserving construct integrity. This capability is increasingly important in globalized doctoral education, where instruments must function across diverse cultural and disciplinary environments (Pelaez-Sanchez et al., 2024). Thus, the integration of AI within MIPI not only modernizes instrument development but also enhances its adaptability and reach.

Ultimately, extending MIPI with AI creates a hybrid framework that preserves the human-centered values of andragogy while leveraging contemporary technological capabilities. The resulting model supports more efficient item generation, more rigorous factor refinement, and more scalable validation processes. Importantly, this extension remains grounded in Henschke's original emphasis on theory–practice congruency, ensuring that technological innovation does not displace the relational and philosophical foundations of adult learning.

Table 1

MIPI-AI: Extended Modified Instructional Perspectives Inventory with AI Integration

Factor No.	Original MIPI Factor	AI-Extended Factor Name	Description	Sample AI-Enhanced Item
1	Planning and Delivery of Instruction	Adaptive Planning and Delivery (AI-Supported)	Uses structured planning enhanced by AI to tailor instruction to learner needs and contexts	The instructor uses AI-supported tools to adapt learning activities based on student needs.
2	Learner-Centered Learning Processes	AI-Enhanced Learner-Centered Processes	Facilitates experiential and self-directed learning with AI-supported resources	The instructor encourages use of AI tools to support independent and self-directed learning.
3	Teacher-Centered Learning Processes	Strategic Instructor-Guided Learning (with AI)	Uses direct instruction when appropriate, supported by AI-generated	The instructor uses AI-generated explanations to clarify complex

			content and examples	concepts when needed.
4	Teacher Empathy with Learners	Empathy and Responsiveness (AI-Informed)	Demonstrates understanding of learner needs using both human interaction and AI insights	The instructor adapts responses based on feedback patterns identified through AI tools.
5	Teacher Insensitivity Toward Learners	AI-Mitigated Instructional Bias (Reverse)	Identifies and reduces bias or insensitivity using AI-supported analysis (reverse-scored)	The instructor ignores learner differences despite available data insights.
6	Accommodating Learner Uniqueness	Personalized Learning Design (AI-Supported)	Adapts instruction to individual differences using AI-driven personalization tools	The instructor uses AI tools to provide personalized learning paths.
7	Teacher Trust of Learners	Trust and Autonomy in AI-Supported Learning	Promotes learner autonomy, including responsible and ethical use of AI tools	The instructor trusts students to use AI responsibly to support their learning.

AI-Extended Subscale Example: Teacher Trust of Learners (MIPI-AI Expansion)

AI-Enhanced Trust Subscale (MIPI-AI) - Likert Scale

Item No.	Statement	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
1	The instructor trusts students to use AI tools ethically in their learning.					
2	The instructor encourages independent problem-solving supported by AI resources.					
3	The instructor expresses confidence in students' ability to evaluate AI-generated information.					
4	The instructor allows students flexibility in					

	using AI to meet learning goals.					
5	The instructor values students' judgment when integrating AI into their work.					
6	The instructor supports students in critically reflecting on AI outputs.					
7	The instructor respects students' autonomy in choosing AI tools for learning tasks.					
8	The instructor provides guidance but does not overly restrict AI use.					

9	The instructor believes students can balance AI assistance with original thinking.					
10	The instructor fosters a learning environment where AI use is transparent and responsible.					
11	The instructor trusts students to disclose and explain their use of AI in assignments.					

Practical Guidelines for Doctoral Students

The integration of artificial intelligence (AI) into doctoral research presents significant opportunities for improving instrument design, efficiency, and methodological rigor. However, effective use of AI requires structured guidance, critical oversight, and ethical awareness. Doctoral students are increasingly experimenting with generative AI tools for brainstorming, drafting, and refining research instruments, yet many lack a systematic process for integrating these technologies responsibly into scholarly practice (Dwivedi et al., 2023). The following guidelines provide a practical framework for doctoral students using AI in instrument development while maintaining theoretical integrity, transparency, and research ethics.

Step-by-Step Process for Using AI in Instrument Design

The first step in AI-supported instrument design is establishing a strong theoretical foundation before engaging any AI system. Students should begin by identifying the conceptual framework guiding the study, such as Henschke's MIPI model or another validated theoretical structure. AI should not determine the constructs; rather, it should support the operationalization of constructs already grounded in literature and theory. Recent scholarship emphasizes that effective AI use in higher education depends on maintaining "human oversight and accountability" throughout the research process

The second step involves using AI to assist with item generation. Once constructs are clearly defined, students may prompt AI systems to generate potential survey items, interview questions, or observational indicators. AI tools can rapidly generate multiple item variations, helping researchers explore different wording styles, reading levels, and contextual adaptations. This stage is particularly useful for overcoming writer's block and expanding initial item pools.

Third, students should engage in human refinement of AI-generated outputs. AI-generated items must be reviewed carefully for clarity, disciplinary appropriateness, and alignment with theoretical constructs. Doctoral researchers should remove vague, redundant, or overly generic items and ensure that generated language reflects the conceptual meaning intended in the study. AI-generated content should be treated as a draft requiring scholarly revision, not as a final product.

The fourth step involves AI-assisted validation and pilot preparation. AI can support early-stage analysis by identifying semantic overlap, readability concerns, or construct inconsistencies. Students may also use AI to simulate participant interpretations of survey items or to identify potential ambiguities before pilot testing. However, traditional validation procedures—such as expert review, pilot testing, reliability analysis, and factor analysis—remain essential.

Finally, students should document and disclose their use of AI throughout the process. Transparent disclosure is increasingly recognized as a critical component of ethical AI use in academic research Proper documentation includes identifying which AI tools were used, how they were used, and the extent of human modification and oversight.

Sample AI Prompts for Instrument Design

One of the practical advantages of AI-supported instrument design is the ability to generate targeted prompts for specific methodological tasks. The following examples demonstrate how doctoral students can use AI productively:

Construct Development Prompt

"Generate five survey items measuring learner trust in an adult education environment based on andragogical principles."

Interview Protocol Prompt

"Develop semi-structured interview questions exploring faculty perceptions of AI integration in doctoral education."

Readability Review Prompt

"Review these survey items for clarity, redundancy, and graduate-level readability."

Cross-Disciplinary Adaptation Prompt

"Adapt these educational leadership survey items for use in healthcare leadership contexts while preserving the original construct."

Bias Identification Prompt

"Identify potential cultural, gender, or linguistic bias in these instrument items."

These prompts illustrate how AI can support both creative and analytical stages of instrument development. Importantly, the quality of AI output depends heavily on the specificity and clarity of prompts provided by the researcher.

Common Mistakes to Avoid

Over-Reliance on AI

One of the most significant risks in AI-supported research is over-reliance on AI-generated content. Recent studies warn that excessive dependence on generative AI may weaken critical thinking, reduce methodological engagement, and encourage passive learning behaviors AI systems can produce convincing but inaccurate or theoretically inconsistent content, commonly referred to as "hallucinations." Therefore, doctoral students must maintain active intellectual engagement throughout the instrument design process.

Researchers should avoid copying AI-generated items directly into instruments without critical evaluation. Instead, AI outputs should function as starting points for scholarly refinement. Human interpretation, contextual understanding, and theoretical judgment remain indispensable.

Misalignment with Theory

Another common problem is the misalignment between AI-generated items and the theoretical framework guiding the study. AI systems generate responses based on probabilistic language patterns rather than conceptual understanding. Consequently, generated items may appear plausible while failing to accurately operationalize the intended construct.

To avoid this issue, students should continuously compare AI-generated items against their theoretical framework and research questions. Every survey item or interview question should be explicitly linked to a construct derived from the literature. This process preserves construct validity and prevents conceptual drift.

Ethical Considerations

Transparency

Transparency is increasingly viewed as a foundational principle of ethical AI use in research Doctoral students should clearly disclose the use of AI in instrument development, including the tools used and the nature of AI assistance. Many universities and publishers now recommend explicit acknowledgment of AI-supported research activities.

Transparent reporting strengthens research credibility and enables evaluators to assess the extent of human oversight in the research process.

Authorship

Current ethical guidelines consistently maintain that AI systems should not be credited as authors because they lack accountability, intellectual responsibility, and agency Human researchers remain fully responsible for all content, interpretations, and conclusions generated with AI assistance. Doctoral students must therefore ensure that AI contributions are appropriately acknowledged without attributing authorship to AI tools.

Bias in AI-Generated Items

AI systems may reproduce or amplify societal biases embedded in training data. Research has shown that AI-generated educational content can reflect cultural, linguistic, gender, or disciplinary biases if not critically reviewed For example, AI-generated survey items may unintentionally privilege dominant cultural assumptions or exclude diverse learner experiences.

To mitigate bias, doctoral students should review AI-generated items through multiple lenses, including inclusivity, accessibility, and cultural sensitivity. Consultation with diverse reviewers and pilot participants is also recommended.

AI-supported instrument design offers doctoral students a powerful methodological resource when used responsibly and critically. By combining theoretical grounding, human oversight, transparent disclosure, and ethical awareness, doctoral researchers can leverage AI to improve efficiency while maintaining scholarly rigor. The future of doctoral instrument design will likely depend not on replacing human expertise, but on developing thoughtful partnerships between human researchers and AI-supported systems, -- with human morality and heartfelt care and love, maintaining overall direction, thus keeping AI guarded and guided within thoroughgoing human agency bounds.

Implications for Research and Practice

The integration of artificial intelligence (AI) into instrument design and doctoral research has significant implications for both research methodology and higher education practice. The proposed AI-Supported Instrument Design (AI-SID) framework extends beyond a technological innovation; it represents a methodological shift toward more scalable, efficient, and accessible approaches to research design. By combining human theoretical grounding with AI-assisted processes, the framework offers practical solutions to longstanding challenges in doctoral research while aligning with emerging trends in higher education and research innovation.

One of the most important implications of the AI-SID framework is the development of a **scalable model for instrument design**. Traditional instrument development processes are often highly individualized, depending heavily on advisor expertise, institutional resources, and researcher experience. This creates inconsistencies in methodological quality across doctoral programs and disciplines. AI-supported systems provide opportunities to standardize portions of the instrument development process while maintaining flexibility for contextual adaptation. Recent studies on AI in higher education emphasize that generative AI technologies can support scalable educational and research practices by increasing accessibility to methodological tools and reducing barriers to entry for novice researchers

The scalability of AI-supported instrument design is particularly important in interdisciplinary research environments. Doctoral students in fields such as education, nursing, business, and leadership studies often struggle to identify frameworks that transfer across disciplinary boundaries. The AI-SID model addresses this issue by preserving a stable theoretical core, such as Henschke's MIPI framework, while using AI to adapt language and contextual examples for different fields. This capacity for contextual adaptation without sacrificing construct integrity increases the broader applicability of research instruments and supports more collaborative and interdisciplinary scholarship.

A second major implication is the potential for **increased rigor and efficiency in doctoral research**. Instrument development is traditionally time-intensive, requiring multiple cycles of item generation, refinement, pilot testing, and validation. AI-assisted processes can significantly reduce the time required for these activities by automating repetitive analytical tasks, such as identifying redundant items, evaluating readability, and generating alternative item wording. Studies examining AI in higher education consistently identify efficiency gains as one of the primary benefits of AI-supported academic work

Importantly, the AI-SID framework does not suggest replacing human judgment with automated systems. Rather, it promotes a hybrid model in which AI enhances human methodological decision-making. This approach strengthens rigor by enabling researchers to engage in more iterative refinement processes and broader exploratory analysis than would otherwise be feasible within doctoral program constraints. AI-supported systems also provide opportunities for more systematic early-stage validation procedures, improving construct alignment and reducing methodological weaknesses before formal statistical testing occurs.

The framework additionally contributes to the **democratization of methodological expertise**. Historically, advanced methodological support has been concentrated among students with access to experienced advisors, well-funded institutions, or extensive research training. AI-supported tools have the potential to reduce these disparities by making sophisticated instrument development support more broadly available. This democratization may help doctoral students from under-resourced institutions or emerging research areas gain access to methodological guidance that was previously inaccessible.

However, recent scholarship cautions that democratization should not be understood merely as increased technological access. Researchers argue that meaningful democratization also requires critical engagement, theoretical understanding, and ethical awareness The AI-SID framework addresses this concern by emphasizing human theoretical grounding as the foundation of all AI-supported processes. In this model, AI expands methodological access without eliminating the need for scholarly expertise and critical thinking.

The democratization of methodological expertise also has implications for doctoral supervision and faculty development. Faculty members may increasingly shift from functioning as sole methodological gatekeepers to serving as mentors who guide students in the responsible and critical use of AI-supported research tools. Emerging research suggests that faculty-guided AI integration produces more reflective and pedagogically meaningful outcomes than unstructured AI use This shift may encourage more collaborative and learner-centered doctoral education practices aligned with andragogical principles.

Finally, the AI-SID framework aligns closely with the **future directions of AI in higher education**. Current research indicates that higher education institutions worldwide are rapidly developing policies, guidelines, and infrastructures for AI integration in teaching, learning, and research AI is increasingly viewed not simply as a technological tool but as a transformative force shaping research practices, educational design, and academic labor. Within this evolving environment, doctoral education must adapt by preparing students to use AI critically, ethically, and effectively.

At the same time, scholars emphasize that AI integration introduces important ethical and epistemological challenges, including concerns about bias, academic integrity, and over-reliance on automation The AI-SID framework responds to these concerns by embedding transparency, human oversight, and theory–practice congruency into the research process. This balance between innovation and responsibility is essential for sustainable AI integration in doctoral research and higher education more broadly.

In conclusion, the AI-SID framework offers important implications for research methodology and doctoral education by providing a scalable, rigorous, and accessible model for instrument design. By combining human-centered theoretical foundations with AI-assisted development processes, the framework positions doctoral researchers to engage more effectively with the evolving landscape of AI-supported higher education.

Conclusion

This article extends Henschke's legacy in adult education (Knowles, 1972; Henschke, 2008, 2017, 2020, 2021) and instrument development by proposing the AI-Supported Instrument Design (AI-SID) framework as a contemporary methodological model for doctoral research. Grounded in the theoretical foundations of the Modified Instructional Perspectives Inventory (MIPI), the framework preserves the human-centered principles of andragogy while integrating AI-assisted processes to improve scalability, efficiency, and methodological rigor. Rather than replacing established theoretical models, AI-SID demonstrates how artificial intelligence can complement and enhance existing frameworks through item generation, refinement, validation support, and cross-disciplinary adaptation.

A central argument of this study is that the future of doctoral instrument design depends on maintaining an intentional balance between **human theory and AI capability**. While AI offers substantial advantages in automating repetitive tasks and accelerating analytical processes, meaningful instrument development still requires human judgment, theoretical grounding, and ethical oversight. Recent scholarship consistently emphasizes that AI in higher education should function as an augmentative tool that supports—not substitutes—critical thinking, scholarly interpretation, and academic integrity.

The AI-SID framework also responds to broader transformations occurring in higher education and doctoral research. As universities increasingly integrate AI into teaching, learning, and research environments, doctoral students will require structured models for ethical and effective AI-supported inquiry. However, significant concerns remain regarding bias, transparency, over-reliance on automation, and the evolving nature of academic work.

Future research should focus on the empirical validation of the AI-SID model across disciplines and educational contexts. Additional studies are needed to examine reliability, construct validity, user perceptions, and ethical implications associated with AI-assisted instrument development. Through such validation, AI-SID may contribute to a more accessible, rigorous, and theoretically grounded future for doctoral research methodology.

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