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Attitudes Toward Artificial Intelligence Beyond Nursing: Psychometric Evidence for ASUAITIN and an Application in U.S. Obstetric Anesthesia Providers

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Abstract

Background

The Attitude Scale Toward the Use of Artificial Intelligence Technologies in Nursing (ASUAITIN) was developed and psychometrically tested in Turkey to measure nurses' attitudes toward artificial intelligence (AI). However, its psychometric evidence has not been synthesized, and its use has been limited to nursing populations. This two-phase instrument adaptation study synthesizes the published psychometric evidence and reports the first application of a lexically adapted ASUAITIN among U.S. obstetric anesthesia providers.

Methods

In Phase 1, psychometric evidence from 14 ASUAITIN studies (original development study, two Chinese validations, and 11 applications) identified by database and forward citation searching was synthesized and appraised using the Consensus-based Standards for the Selection of Health Measurement Instruments (COSMIN) taxonomy. Reported statistics were checked within each study and against cited sources. In Phase 2, a lexically adapted ASUAITIN was administered to 38 obstetric anesthesia providers (30 certified registered nurse anesthetists, 8 physician anesthesiologists) and analyzed for item performance and internal consistency (Cronbach's alpha with 95% CI).

Results

Phase 1: Subscale internal consistency was high across three psychometric studies (α = 0.885 to 0.948) whereas total-scale values were more variable (α = 0.712 to 0.976); two studies reported test-retest reliability, and none reported measurement error. Both Chinese validations replicated the two-factor structure, but neither confirmatory factor analysis met conventional thresholds across all fit indices. Source verification identified reporting discrepancies, including factor loadings misreported as item-total correlations, psychometrically implausible values, and an unstated scoring direction. Phase 2: The mean total score was 54.79 (SD 6.38; range 39 to 72). Cronbach's α was 0.868 for the total scale, 0.842 for the negative subscale, and 0.823 for

the positive subscale, with all corrected item-total correlations exceeding 0.30, supporting the reliability of the scale in the current sample.

Conclusions

Published evidence supports subscale reliability and a replicated two-factor structure, but hypothesis testing is limited, and measurement error, responsiveness, and invariance across languages, professions, and settings remain untested. The lexically adapted ASUAITIN showed internal consistency comparable to that reported in nursing samples; however, formal adaptation and validation in an adequately powered study are needed.

Keywords: Artificial Intelligence (AI); Obstetric Anesthesia; ASUAITIN; Psychometrics; Attitudes on AI; Nurse Anesthetists

Background

Artificial intelligence (AI) has rapidly emerged as a transformative force in nursing practice, education, and clinical decision-making [1]. As algorithmic systems become embedded in electronic health records, patient monitoring, and workflow optimization, nurses' acceptance of and trust in these technologies have become critical determinants of successful implementation [2]. Measuring nurses' attitudes toward AI can inform strategies for education, policy, and system design [3, 4].

These questions extend to anesthesia, where AI-enabled monitoring, prediction, and decision support are entering perioperative and obstetric care [5, 6]. Surveys of physician anesthesiologists report cautious optimism alongside concerns about transparency, professional role, and ethics, whereas evidence on nurse anesthetists is sparse [7, 8]. In the United States, certified registered nurse anesthetists (CRNAs) and physician anesthesiologists provide obstetric anesthesia, either independently or in anesthesia care team settings. Because CRNAs are advanced practice nurses, instruments developed to measure nurses' attitudes toward AI are a logical starting point for measuring attitudes in this population. However, no psychometrically evaluated instrument has been specifically adapted for assessing attitudes toward AI among obstetric anesthesia providers, creating a need to examine whether existing nursing-based measures can be extended to this setting.

The Attitude Scale Toward the Use of Artificial Intelligence Technologies in Nursing (ASUAITIN), first published in *BMC Nursing* in 2025 by Yılmaz and colleagues, is the first known psychometrically tested instrument specifically developed for nurses in this field [9]. The ASUAITIN consists of 15 items organized into two subscales (positive and negative attitudes toward AI) and is measured on a five-point Likert scale, with higher scores indicating more favorable attitudes. The instrument has now appeared in international validations and applied studies, including two English-language Chinese validations [10, 11] and 11 applied studies

[12–22]. No review has yet synthesized the psychometric evidence accumulating across those uses.

The original ASUAITIN instrument was developed among nurses working in medical, surgical, and intensive care settings in Turkey [9]. Its 15 items address AI in relation to patient safety, ethics, the profession, routine clinical procedures, and professional training, all of which apply to anesthesia practice, and its brevity suits administration within a larger study. Extending it to anesthesia providers is nonetheless a two-part step. CRNAs share the nursing background around which the instrument was built but practice within a different clinical scope, whereas physician anesthesiologists share that clinical scope but not the nursing background. Because several items are written around features of nursing practice, their meaning in anesthesia cannot be assumed. At the same time, ASUAITIN has accumulated psychometric evidence in two countries, making it a logical candidate for adaptation rather than development of a de novo measure. Extending it beyond its original population depends on both the strength of that evidence and the nature of the proposed adaptation.

The objective of this two-phase instrument adaptation study was to (1) synthesize and critically evaluate the psychometric evidence for ASUAITIN across its translated, replicated, and applied uses, with the Artificial Intelligence Attitude Scale for Nurses (AIAS) as a comparator [23], to inform its adaptation for obstetric anesthesia providers, and (2) conduct the first descriptive application of the lexically adapted instrument among U.S. obstetric anesthesia providers.

Conceptual Framework for Instrument Adaptation and Evaluation

The present study was informed by recommendations from the scale adaptation literature and by Consensus-based Standards for the Selection of Health Measurement Instruments (COSMIN) guidance for evaluating measurement properties [24]. Heggestad et al. describe context adaptation as the application of an existing instrument to a new setting or

population through modification of item referents while preserving the underlying construct [25]. Accordingly, this study first synthesized the psychometric evidence supporting ASUAITIN using COSMIN domains and then examined a preliminary context adaptation of the instrument among U.S. obstetric anesthesia providers. This sequential approach reflects the two-phase design, in which evidence synthesis informed instrument adaptation and initial evaluation in the target population.

COSMIN guidance organizes nine measurement properties into three domains (reliability, validity, and responsiveness) and treats interpretability as an important characteristic of an instrument rather than a measurement property; these properties should be evaluated when considering use of an instrument across settings, languages, cultures, or populations [26]. Within the reliability domain, internal consistency is the degree of interrelatedness among items, commonly estimated with Cronbach's alpha [27, 28]; reliability is the proportion of total variance in scores attributable to true differences between respondents, assessed through test-retest, inter-rater, or intra-rater designs and commonly estimated with the intraclass correlation coefficient; and measurement error is the systematic and random error in a score that is not attributable to true change in the construct [29]. Within the validity domain, content validity is the degree to which item content adequately reflects the construct, is typically established through expert review, and includes face validity [30–32]. Construct validity comprises structural validity, the degree to which scores reflect the dimensionality of the construct [28]; hypotheses testing, the degree to which scores are consistent with prespecified hypotheses about relationships with other measures or differences between groups; and cross-cultural validity/measurement invariance, the degree to which items perform equivalently across translated or culturally adapted versions or across groups [26, 29]. Criterion validity, the degree to which scores reflect a "gold standard," is not applicable here because no gold standard exists for attitudes toward AI. Responsiveness is the ability of an instrument to detect change over time in the construct measured, and interpretability is the degree to which qualitative meaning can be assigned to

scores or changes in scores [29]. The framework is used here to evaluate the extension of ASUAITIN from the bedside nursing populations in which it was originally developed and validated to the obstetric anesthesia context involving both advanced practice nurse anesthetists and physician anesthesiologists. Within this framework, the evidence synthesis evaluates the existing psychometric foundation of the instrument, whereas the anesthesia-provider application represents an initial context adaptation involving changes in both professional referent and clinical practice setting.

Methods

Phase 1: Psychometric Evidence Synthesis

A targeted psychometric evidence synthesis was conducted, with measurement properties extracted and evaluated according to COSMIN domains as a framework for evidence appraisal rather than as a compliance standard [26]. Databases searched were PubMed and Google Scholar in August 2026. The final search strategy was designed to capture all publications using ASUAITIN and was executed using the Boolean string:

Attitude Scale toward* the Use of Artificial Intelligence Technolog* in Nursing

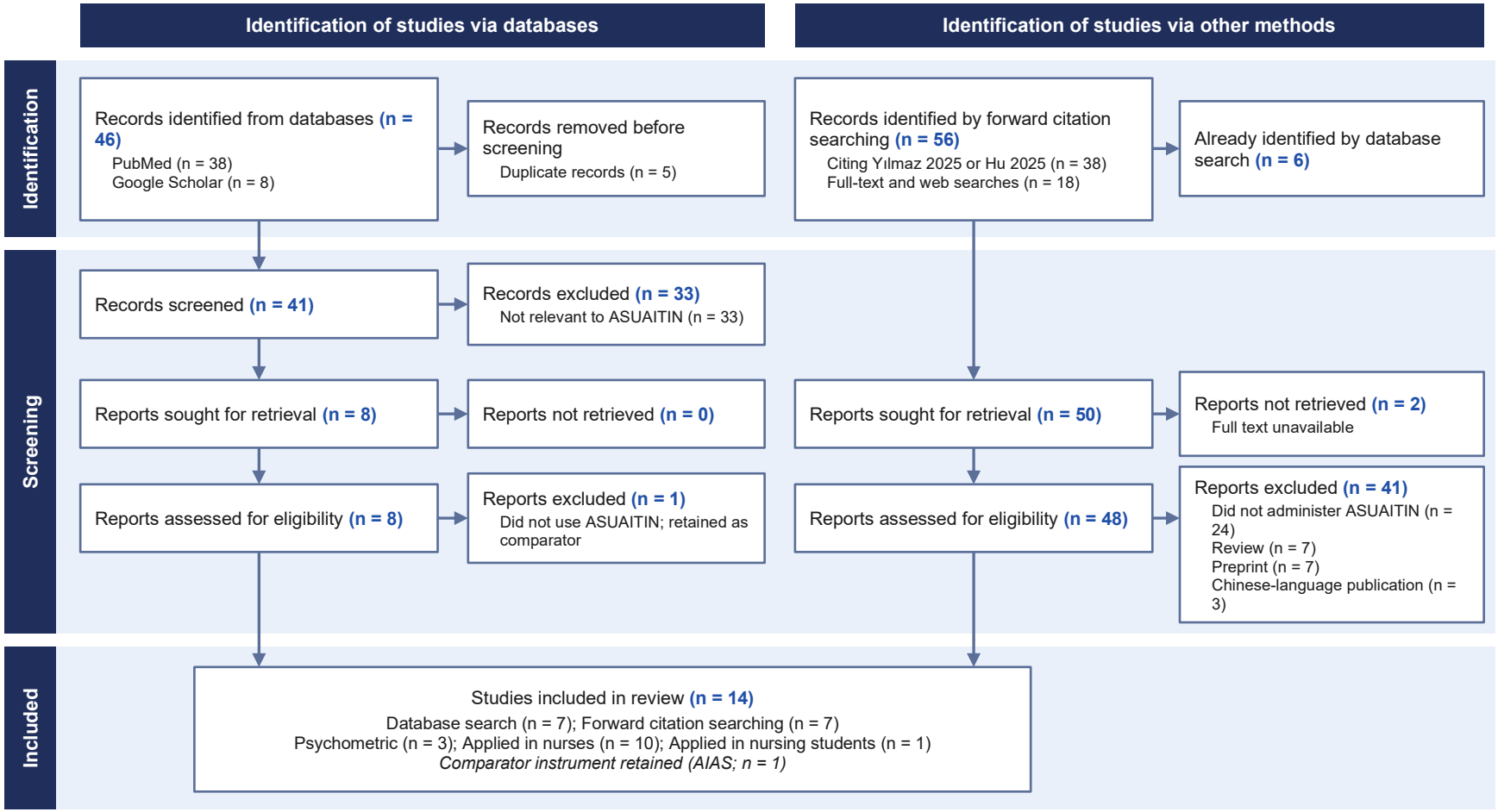
The search produced 46 records. After the removal of five duplicates, 41 records were screened by title and abstract, and eight were retrieved for full-text review. Inclusion criteria were: (1) empirical, peer-reviewed articles published in English; (2) original development, validation, or analytical application of ASUAITIN; and (3) nursing-specific samples, comprising practicing nurses or nursing students, with nursing-student samples extracted and reported separately. Exclusion criteria included editorials and studies using unrelated attitude scales. Although no time frame was specified, all relevant studies were published in 2025 and 2026, coinciding with the initial release of the ASUAITIN instrument.

Because instrument names in applied studies often appear only in the methods section, which bibliographic databases do not index, the database search was supplemented by forward citation searching. The 56 records identified were assessed against the same criteria. Six were

studies already included, and seven met the inclusion criteria; 41 were excluded because they did not administer ASUAITIN (n = 24), were reviews (n = 7), were preprints (n = 7), or were Chinese-language validations that did not meet the English-language criterion (n = 3) [33–35]. Two records were excluded because they could not be retrieved in full text.

Fourteen studies met the inclusion criteria, seven from the database search and seven from forward citation searching. Three reported psychometric evaluation of the instrument: the original Turkish development and validation by Yılmaz et al. [9], the Chinese translation and validation by Hu et al. [10], and a second Chinese cross-cultural adaptation and psychometric analysis by Chen et al. (2026) [11]. Eleven applied the instrument without a primary aim of evaluating its measurement properties: From the database search, Chen et al. (2025) [12] and Xu et al. [13] modeled ASUAITIN as a construct within mediation analyses, Yu et al. [14] administered it alongside measures of AI literacy and change fatigue, and Ma and Wang [15] used it in a latent profile analysis. Of the seven studies identified by forward citation searching, five modeled ASUAITIN within mediation or latent profile analyses [17–20, 22], one compared scores across nurse characteristics [16], and one administered it to nursing students [21]. One of these reports appears to draw on the same survey as Yu et al. [14, 19]. The two Turkish applied studies used the original instrument [16, 17], Wang et al. [22] used a separate Chinese adaptation reported in a Chinese-language journal [33], and the remaining Chinese applied studies used the version of Hu et al. [10] or did not specify one. An additional full-text article from the database search, Yıldırım and Karaman's development of the AIAS, did not use ASUAITIN and therefore did not meet inclusion criteria. It was retained as a comparator because it measured the same construct, used a similar nurse population, and reported more extensive psychometric procedures [23]. The search and screening process is summarized in flow diagram format (Figure 1).

Figure 1. Search Flow Diagram



Note. PRISMA flow diagram of the study selection process illustrates the literature search and screening strategy. The initial database and forward citation searches yielded raw records, which were subsequently deduplicated. Studies were then screened for ASUAITIN relevance. Articles were excluded if they were preprints or reviews, full text could not be retrieved, and they are non-English language publications. A total of 14 articles were included in the final review. One comparator, AIAS, was retained.

Data were extracted into a standardized table of evidence (Table 1). Reported psychometric evidence was extracted, categorized according to the COSMIN taxonomy described above [29]. Each property was recorded for each study as reported, not reported, or not applicable (Table 2). In addition, reported statistics were checked for internal consistency within each study, comparing values given in the abstract, text, and tables, and for consistency with the source study where a value was attributed to prior work. Discrepancies identified through this process are reported alongside the extracted values rather than resolved.

The inclusion and exclusion criteria described above govern the evidence synthesis only. The anesthesia-provider instrument data reported in Phase 2 constitute original primary data and are presented separately from the Phase 1 evidence synthesis. Findings from Phase 1 informed the decision to pursue lexical adaptation of ASUAITIN for use among obstetric anesthesia providers, which is described in Phase 2.

Phase 2: Lexical Instrument Adaptation and Initial Application in U.S. Obstetric Anesthesia Providers

This component of the study involved an initial context adaptation and application of ASUAITIN using instrument data collected within a larger mixed-methods study of obstetric anesthesia providers' risk reasoning and feelings about AI (IRB STUDY00009239). The parent study was not designed as a psychometric investigation, and the adapted ASUAITIN was administered as one component of a broader instrument battery. Because the validity evidence recommended for context adaptations was not collected [25], the analyses reported here are exploratory and descriptive rather than a formal psychometric validation.

Participants were CRNAs and physician anesthesiologists practicing obstetric anesthesia in the United States and were recruited between April 2026 and July 2026 via convenience sampling under the parent study's eligibility criteria. Eligibility criteria required participants to be licensed CRNAs or physician anesthesiologists with a minimum of three years of clinical experience, have at least 50% of their practice dedicated to obstetric anesthesia, and

be currently practicing in the United States or its territories. Providers-in-training (e.g., residents, fellows) and individuals unable to communicate fluently in English were excluded due to comprehension and analysis requirements. The instrument data were collected and managed using REDCap (Research Electronic Data Capture) electronic data capture tools hosted at Emory University [36, 37]. Participants completed eligibility screening, a demographic questionnaire, and informed consent, then completed the adapted ASUAITIN tool prior to scheduling their qualitative interview.

Forty instrument responses were received. Two participants submitted the instrument twice following errors in REDCap personal data entry; in each case, the complete entry associated with study admission was retained, and the earlier entry was removed. The analytic sample comprised 38 providers, of whom 30 were certified registered nurse anesthetists, and 8 were physician anesthesiologists. All participants in the analytic sample completed all 15 items, and no item responses were missing.

Written permission to adapt the ASUAITIN and to report findings from the adapted version was obtained from Prof. Dr. Dilek Yılmaz, corresponding author of the original instrument. The study team adapted the instrument for use with anesthesia providers through lexical substitution only. In each of the 15 items, the terms "nursing," "nursing care," and "nurses" were replaced with "anesthesia" and "anesthesia providers." Item content, item order, response format, and scoring were otherwise unchanged, and the illustrative examples within items were left as written in the source instrument. In the taxonomy of scale adaptations described by Heggestad et al., the modification is best classified as a lexically adapted ASUAITIN involving changes in item referents while preserving the underlying construct and instrument structure [25].

The ASUAITIN was developed and validated in Turkish [9]. The English item wording used here is the version published by the developers as supplementary material to the development study; the developers do not report who translated the items or how, and the

English version has not been validated. The study team performed no further translation, and the equivalence of the English wording to the Turkish items was not examined. No expert committee review, cognitive interviewing, content validity indexing, or pilot testing was conducted for the adapted version, and no psychometric evaluation of the adapted instrument was undertaken prior to administration. The version used in this study is therefore described as a lexically adapted ASUAITIN rather than a formally adapted and validated instrument.

Each item was scored on a five-point Likert scale. The six items comprising the negative attitude subscale (items 1 through 6) were reverse-scored so that higher values indicated more favorable attitudes, and the nine items comprising the positive attitude subscale (items 7 through 15) were scored as recorded. Total scores were calculated as the sum of all 15 items following reverse-scoring, with a possible range of 15 to 75 and higher scores indicating more favorable attitudes toward artificial intelligence.

Analyses were confined to item-level descriptive statistics and internal consistency. Item means, standard deviations, and response distributions were calculated for each of the 15 items. Corrected item-total correlations were computed against the reverse-scored total. Cronbach's alpha was calculated with a 95% confidence interval (CI) for the total scale and for both subscales using bias-corrected and accelerated bootstrap resampling (10,000 resamples, seed 2026) in the MBESS package, with a percentile bootstrap computed independently as a corroborating check. Values were compared descriptively against those reported in the studies reviewed in the evidence synthesis. Alpha with each item removed is reported descriptively. No items were deleted or modified, as the instrument was treated here as fixed rather than under development. Analyses were conducted in R 4.5.2 using psych 2.6.1 and MBESS 5.0.1.

No factor analysis was conducted. The sample size recommendation applied in the development of ASUAITIN specifies ten participants per item, which corresponds to 150 participants for a 15-item instrument [9], and the present sample does not approach that threshold. No claims regarding factor structure are therefore made. Measurement invariance

and differential item functioning across provider type were not examined as sample size requirements for these procedures exceed the available data, and the subgroup of eight physician anesthesiologists was insufficient to support meaningful group comparison. Descriptive statistics are reported separately for CRNAs and physician anesthesiologists, and no inferential comparison between provider groups was performed.

Results

Phase 1: Findings from Published ASUAITIN Studies

Table 2 summarizes the measurement properties reported across the 14 ASUAITIN studies and the AIAS comparator, organized by the COSMIN taxonomy, with studies grouped as psychometric, applied in nurses, applied in nursing students, and a comparator. Within the reliability domain, internal consistency was reported in three psychometric studies, ten applied samples, and the comparator [9–12, 14–23]; reliability was assessed only as test-retest reliability in two samples and the comparator [10, 11, 23], and no study reported measurement error. Within the validity domain, content validity was reported in three samples and the comparator [9–11, 23], and two studies described pretests of item clarity as evidence of face validity [11, 21]. For construct validity, structural validity was examined in five samples and the comparator [9–11, 13, 21, 23]; the two-factor structure was replicated in both Chinese validations [10, 11], whereas Xu et al. modeled ASUAITIN together with three other constructs [13]. Hypotheses testing was reported in all 11 applied samples [12–22], although no study prespecified hypotheses as a test of validity, and cross-cultural validity/measurement invariance was tested in one sample, across AI-exposure groups rather than languages or cultures [11]. Criterion validity was not applicable because no gold standard exists. No study assessed responsiveness. Score distributions supporting interpretability were reported in all 14 studies and the comparator [9–23], but no study reported floor or ceiling effects or a minimal important change. No study has administered the instrument outside nursing. The only change of population was to nursing students for whom the professional referent remained nursing [21].

The sections that follow present the evidence in the same order, and inconsistencies identified during extraction are summarized at the end of this section.

Table 2. Measurement properties reported in ASUAITIN studies, by COSMIN taxonomy

	Psychometric studies			Applied studies: nurses										Nursing students	Comparator
Measurement property	**Yılmaz 2025 [9]**	**Hu 2025 [10]**	**Chen 2026 [11]**	**Chen 2025 [12]**	**Xu 2026 [13]**	**Yu 2026 [14]**	**Ma & Wang 2026 [15]**	**Wang 2026 [22]**	**Taşçı 2026 [16]**	**Üzen Cura 2026 [17]**	**Li 2026 [18]**	**Yu 2026[l] [19]**	**Wei 2026 [20]**	**Yi 2026 [21]**	**Yıldırım 2025 [23]**
Identified by	DB	DB	DB	DB	DB	DB	DB	FC	FC	FC	FC	FC	FC	FC	DB
Reliability															
Internal consistency	✓	✓	✓	✓	NR[a]	✓	✓	✓	✓	✓	✓[b]	✓	✓	✓	✓
Reliability: test-retest	NR	✓[c]	✓[d]	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR[a]	NR[a]	✓
Reliability: inter-rater/intra-rater	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Measurement error	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
Validity															
Content validity	✓	✓	✓	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	✓
Face validity (content validity)	NR	NR	✓[e]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	✓[e]	NR
Construct: structural validity	✓[f]	✓	✓	NR	✓[g]	NR	NR	NR	NR	NR	NR	NR	NR	✓[h]	✓
Construct: hypotheses testing[i]	NR	NR	NR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	NR
Construct: cross-cultural validity/measurement invariance	NR	NR	✓[j]	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
Criterion validity	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Responsiveness	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
Interpretability[k]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note. Properties and labels follow the COSMIN taxonomy. ✓ = reported; NR = not reported; NA = not applicable. Content and face validity are coded NA for applied studies that adopted a published version without modification. Composite reliability, average variance extracted, and comparisons of factor models were coded as structural validity; hypotheses testing was coded when ASUAITIN scores were related to other constructs or compared across groups; interpretability was coded when score distributions (total, subscale, or item level) were reported. Full citations for each study are given in Table 1. DB = identified by database search; FC = identified by forward citation searching. [a]Not estimated in the study sample; the authors cite the coefficients of Hu et al. [10]. [b]Subscale coefficients reported without stating whether they were estimated in the study sample; no total-scale coefficient. [c]The abstract reports a two-month interval and a total ICC of 0.91; the body text reports two weeks and 0.992. [d]Coefficient type not named; no confidence intervals. [e]Pretest of item clarity described by the authors as evidence of face validity. [f]Exploratory factor analysis only. [g]Confirmatory factor analysis only, with ASUAITIN modeled together with three other constructs. [h]Confirmatory factor analysis in 259 nursing students: $\chi^2/df = 3.10$, GFI = 0.883, RMSEA = 0.090; CFI and TLI not reported. [i]No study prespecified hypotheses as a test of validity; Chen et al. [12], Xu et al. [13], and Wang et al. [22] stated directional study hypotheses without expected magnitudes. [j]Invariance tested across self-reported AI-exposure groups within one sample, not across languages or cultures; the scalar chi-square difference test for hospital adoption was

significant, and invariance was accepted on changes in CFI and RMSEA. [k]*Not a measurement property in COSMIN; no study reported floor or ceiling effects or a minimal important change.* [l]*Appears to report the same survey as Yu et al. [14]; samples are not independent.*

Subscale alpha was high in all three psychometric studies (0.885 to 0.948), and Chen et al. (2026) additionally reported McDonald's omega (0.920 and 0.931), the only alternative internal consistency estimate in any ASUAITIN study (Table 3) [9–11]. Total scale alpha was lower and more variable, ranging from 0.712 to 0.976 across 10 independent nurse samples and 0.862 in nursing students [21]; in Hu et al., the total scale value (0.785) fell below both of its own subscale values [10], and Xu et al. reported the coefficients of Hu et al. rather than calculating their own [13]. Among studies that reported a total-scale coefficient, only Taşçı et al. stated a scoring direction, reporting that no items were reverse-scored [16]. Xu et al. scored the negative items forward and analyzed the two subscales separately [13], and Yu et al. summed the two subscales into a total after reporting that they correlated at r = -0.916 [19]. Two studies assessed test-retest reliability over two-week intervals (Table 4): Hu et al. in 30 nurses and Chen et al. (2026) in 50 nurses, the latter without confidence intervals [10, 11]. In Hu et al., the total scale intraclass correlation coefficient (0.992) was far higher than either subscale coefficient (0.742 and 0.710) [10]. No study reported measurement error, such as the standard error of measurement or the smallest detectable change.

Table 3. Internal consistency reliability reported for ASUAITIN across studies

Study	Sample	Total scale	Negative subscale	Positive subscale
Yılmaz et al. 2025 (development)	200 Turkish nurses	0.910	0.933	0.917
Hu et al. 2025 (validation)	499 Chinese nurses	0.785	0.920	0.948
Chen et al. 2026 (validation)	436 Chinese nurses	0.890	0.885	0.933
Chen et al. 2025 (applied)	564 Chinese nurses	0.747	NR	NR
Xu et al. 2026 (applied)	436 Chinese nurses	cited from Hu	cited from Hu	cited from Hu
Yu et al. 2026 (applied)	449 Chinese nurses	0.845	NR	NR
Ma and Wang 2026 (applied)	715 Chinese nurses	0.712	0.704	0.712
Wang et al. 2026 (applied)	765 Chinese nurses	0.885	NR	NR
Taşçı et al. 2026 (applied)	368 Turkish nurses	0.830	0.850	0.835
Üzen Cura et al. 2026 (applied)	301 Turkish nurses	0.976	0.927	0.956
Li et al. 2026 (applied)	366 Chinese nurses	NR	0.890	0.932
Yu et al. 2026 (applied)	460 Chinese nurses	0.845	NR	NR
Wei et al. 2026 (applied)	206 Chinese nurses	0.784	NR	NR
Yi et al. 2026 (applied)	259 Chinese nursing students	0.862	NR	NR
Present study	38 U.S. anesthesia providers	0.868	0.842	0.823

Note. Values are Cronbach's alpha as reported in each study. NR = not reported. Chen et al. (2026) also reported McDonald's omega of 0.920 and 0.931 for the negative and positive subscales. Chen et al. (2026) conducted analyses in two randomly assigned subsamples of 218 [11]. Subscale designations follow the original two-factor structure: negative attitude, items 1 through 6; positive attitude, items 7 through 15. "Cited from Hu" indicates that Xu et al. reported the coefficients of Hu et al. rather than calculating their own [13]. Li et al. reported subscale coefficients without stating whether they were estimated in their sample [18]. Yi et al. sampled nursing students [21]. In the present study, negative attitude items were reverse-scored before the total was computed; the 95% confidence interval (CI) for total alpha was 0.768 to 0.925.

Table 4. Temporal stability assessed by ASUAITIN studies

Study	Sample	Total scale ICC	Negative subscale ICC	Positive subscale ICC
Hu et al. 2025 (validation)	30 Chinese nurses	0.992 (0.984–0.996)	0.742 (0.527–0.868)	0.710 (0.475–0.850)
Chen et al. 2026 (validation)	50 Chinese nurses	0.924	0.864	0.937

Note. Values for Hu et al. are intraclass correlation coefficients (ICC) [10]; Chen et al. (2026) reported test-retest coefficients without naming the coefficient type [11]. Values in parentheses are 95% CI; Chen et al. (2026) did not report CIs [11]. Both studies used a two-week retest interval (for Hu et al., per the body text; the abstract states two months and a total ICC of 0.91) [10, 11]. The remaining 12 ASUAITIN studies did not assess temporal stability.

All three psychometric studies used expert review, but with different panels, procedures, and indices: Yılmaz et al. calculated content validity ratios from 15 experts [9], Hu et al. reported an average item-level content validity index of 0.87 and a scale-level index of 0.91 from 12 experts [10], and Chen et al. (2026) used an 11-member Delphi panel (item-level indices 0.909 to 1.000, scale-level average 0.994) followed by a pretest with 15 clinical nurses [11]. The content validity evidence is therefore not directly comparable across versions, and the versions themselves differ. Hu et al. reworded item 8 to refer to future rather than current applications, citing limited current use of AI in Chinese nursing practice [10], and Chen et al. (2026) revised items 1, 3, 4, and 13, including a change in the content of item 1 from hindrance to “the application of nursing care practices to detriment to “the development of nursing work,” changed the key term in item 11 from prediction to preassessment, and reported further unspecified wording changes to other items [11]. Among applied studies, Yi et al. pretested the version of Hu et al. with 15 nursing students for comprehensibility only [21]

All three psychometric studies recovered the two-factor structure, with the six negative attitude items and the nine positive attitude items loading on separate factors that together explained 67.8% to 73.3% of variance [9–11]. The two Chinese studies tested this structure with confirmatory factor analysis in independent subsamples. Hu et al. reported a comparative fit index (CFI) of 0.897 and a Tucker-Lewis index (TLI) of 0.878, evaluated against a stated criterion of 0.80 for CFI and TLI and 0.10 for the root mean square error of approximation (RMSEA) [10], and Chen et al. (2026) reported an RMSEA of 0.090, with a 90% CI extending to 0.103, evaluated against a stated criterion of 0.10 [11]. Both sets of authors described the fit as acceptable. Chen et al. (2026) also found that a two-factor model fit better than a single-factor model, and noted that because the two factors align with the polarity of item wording, a wording effect cannot be excluded [11]. In the applied studies, Yi et al. fit the two-factor model in 259 nursing students ($\chi^2/df = 3.10$, GFI = 0.883, RMSEA = 0.090; CFI and TLI not reported) [21].

Beyond structural validity, evidence relevant to hypotheses testing is indirect: no study prespecified expected relationships as a test of validity, and none stated expected magnitudes. Chen et al. (2025) reported positive correlations between ASUAITIN scores and eHealth literacy, technology trust, and perceived value (r = 0.472 to 0.637) [12], and Xu et al. reported composite reliability above 0.70, average variance extracted above 0.50, and discriminant evidence based on average variance extracted for ASUAITIN within a model of related constructs [13]. That evidence shows ASUAITIN is separable from constructs expected to be related to it but does not test its association with unrelated constructs. Xu et al. also reported Spearman correlations of the negative and positive subscales with AI anxiety (p= 0.775 and −0.328) and with AI literacy (p = 0.095 and 0.249) [13]. Yu et al. examined ASUAITIN scores as an outcome of AI literacy, change fatigue, and workplace characteristics in multiple regression, and Ma and Wang compared ASUAITIN scores across AI-anxiety profiles, with higher scores associated with membership in lower-anxiety profiles [14, 15]. In the studies identified by forward citation searching, ASUAITIN scores correlated with technology acceptance constructs and innovativeness (r = 0.505 to 0.622) [22], with AI literacy (r = 0.571) and change fatigue (r = −0.558) [19], and with professional values through the positive subscale only (r = 0.352; negative subscale r = −0.021) [17]. Group comparisons and latent profile analyses related scores to AI training, AI literacy profiles, and generational characteristics [16, 18, 20], and in nursing students the two subscales correlated with creative self-efficacy in opposite directions (p = 0.316 and −0.159) [21]. Wang et al. also stated directional hypotheses; none of these studies specified expected magnitudes [22].

Chen et al. (2026) tested configural, metric, and scalar invariance across three self-reported groupings, awareness of AI in healthcare, awareness of AI in nursing practice, and hospital adoption of AI, and reported invariance supported at all three levels on the basis of changes in CFI and RMSEA, although the chi-square difference test for scalar invariance by hospital adoption was significant ($\Delta\chi^2 = 31.412$, $\Delta df = 13$, $p = 0.003$). The groupings rested on

single-item questions, and no study has tested invariance across languages, cultures, clinical practice settings, or professional groups [11]. Criterion validity was not applicable, and responsiveness was not assessed in any ASUAITIN study. No study reported floor or ceiling effects or a minimal important change to support interpretability.

Source verification identified several reporting discrepancies. Hu et al. report the item-total correlation range of the Turkish development study as 0.529 to 0.866, which corresponds to the factor loadings printed by Yılmaz et al., whose item-total correlations are 0.504 to 0.870 [9, 10]. Hu et al. state the test-retest interval and coefficient as two months and 0.91 in the abstract but as two weeks and 0.992 in the methods, results, and discussion [10]. The development study and both Chen et al. publications state a minimum obtainable score of 5, although the minimum for 15 items scored 1 to 5 is 15 [9, 11, 12]. Several printed values are not psychometrically possible. Hu et al. report a confirmatory model with 169 degrees of freedom, whereas a 15-item scale cannot exceed 120 (89 for the standard two-factor specification), and report an average item-level content validity index (0.87) that differs from the scale-level average (0.91), although the two are equal by definition [10, 30]. Yu et al. report a maximum of 32 on the six-item negative subscale, whose possible maximum is 30 [19]. Üzen Cura et al. report a total alpha (0.976) above both subscale alphas (0.927 and 0.956), although the subscales correlated negatively ($r = -0.169$) and the total alpha implied by the reported subscale statistics is approximately 0.85 [17].

The AIAS, published in the same journal about ten weeks after ASUAITIN, measures the same overarching construct with 32 items on four factors: nursing care, organization, ethics, and AI readiness [9, 23]. Its development study reported content validity indices, split-sample exploratory ($n = 332$) and confirmatory ($n = 346$) factor analyses, a total scale alpha of 0.925, test-retest reliability with a confidence interval (intraclass correlation coefficient 0.947, 95% CI 0.887 to 0.975), and composite reliability and average variance extracted for all four factors [23]. Two features limit the comparison: the AIAS covers a broader domain with roughly twice as

many items, and it was developed and validated in Turkish and translated into English only for reporting, a limitation its authors acknowledge. The AIAS authors cite the ASUAITIN development study, but no study identified in this review has compared the two instruments empirically [23].

Phase 2: Lexical Instrument Adaptation and Initial Application in U.S. Obstetric Anesthesia Providers

The analytic sample comprised 38 providers (30 CRNAs and 8 physician anesthesiologists), all of whom completed all 15 items. Results are reported as scale-level and item-level descriptive statistics, followed by internal consistency and scores by provider type.

Scale scores

The mean total scale score was 54.79 (SD 6.38, median 55), with observed scores ranging from 39 to 72. No participant scored at either extreme of the possible range, and 92.1% scored above the scale midpoint of 45, indicating generally favorable attitudes with no scale-level floor or ceiling effect. The negative attitude subscale averaged 20.79 (SD 3.71, observed range 12 to 28) and the positive attitude subscale averaged 34.00 (SD 3.67, observed range 23 to 44), corresponding to mean per-item scores of 3.46 and 3.78, respectively. The two subscale sums correlated at r = 0.50.

Item performance

Item-level means, standard deviations, medians, response distributions, and floor and ceiling percentages for all 15 items are reported in Table 5. Item means ranged from 2.89 to 4.16. The two highest-scoring items concerned wanting training in and skills for using AI in anesthesia (means 4.16 and 4.13), which also showed the highest ceiling percentages (18.4% and 21.1%). The only item with a mean below the response midpoint of 3 was the statement that AI use in anesthesia practice can cause ethical problems (mean 2.89); it was the only item with no respondent selecting the most favorable option, and the only item whose observed

maximum was 4 rather than 5. Item-level floor responses were rare, exceeding 5% for that item alone.

Internal consistency

Cronbach's alpha was 0.868 (95% CI 0.768 to 0.925) for the total scale, 0.842 (0.742 to 0.908) for the negative attitude subscale, and 0.823 (0.700 to 0.902) for the positive attitude subscale. Corrected item-total correlations ranged from 0.349 to 0.758, with all 15 items exceeding the conventional 0.30 threshold (Table 5). Alpha with individual items removed ranged from 0.848 to 0.868; removing any item would not have increased total-scale alpha above its observed value.

Provider type

Total scores averaged 55.40 (SD 6.26) among CRNAs (n = 30) and 52.50 (SD 6.74) among anesthesiologists (n = 8). These are reported descriptively; no statistical comparison was conducted.

Table 5. Item-level descriptive statistics and reliability indices for the adapted ASUAITIN (N = 38)

#	Item	M	SD	Mdn	Range	Floor %	Ceiling %	r item-total	α if deleted
1[a]	I think artificial intelligence technologies will be a hindrance to the application of anesthesia practices.	3.55	0.80	4	1–5	2.6	5.3	0.461	0.863
2[a]	I feel uncomfortable when I think how artificial intelligence technologies will be used in the future in anesthesia care.	3.34	0.97	3.5	1–5	2.6	7.9	0.658	0.852
3[a]	I think that the anesthesia profession will be harmed if artificial intelligence technologies are used more in the future.	3.66	0.75	4	2–5	0.0	10.5	0.567	0.858
4[a]	I think that the use of artificial intelligence technologies in anesthesia care will put patient safety at risk.	3.55	0.72	4	2–5	0.0	5.3	0.758	0.848
5[a]	I think it isn't right to use artificial intelligence technologies in anesthesia.	3.79	0.84	4	2–5	0.0	15.8	0.516	0.861
6[a]	I think that the use of artificial intelligence technologies in anesthesia practice can cause ethical problems.	2.89	0.86	3	1–4	5.3	0.0	0.451	0.865
7	Artificial intelligence technologies can provide new opportunities for anesthesia providers.	3.95	0.57	4	2–5	0.0	10.5	0.491	0.862
8	The field of use of artificial intelligence technologies in anesthesia is wide.	3.37	0.82	3	2–5	0.0	5.3	0.579	0.857

#	Item	M	SD	Mdn	Range	Floor %	Ceiling %	r item-total	α if deleted
9	There are many beneficial applications of artificial intelligence technologies in anesthesia.	3.53	0.69	4	2–5	0.0	5.3	0.495	0.861
10	I would prefer to use a system with artificial intelligence for some routine anesthesia procedures, like vital findings and pain assessment.	3.47	0.83	4	1–5	2.6	5.3	0.409	0.866
11	Predictions about the patient by artificial intelligence technologies (anesthesia diagnosis, care needs, etc.) can provide practical opportunities to make the profession easier.	3.74	0.64	4	1–5	2.6	2.6	0.424	0.864
12	I think that benefitting from artificial intelligence technologies in anesthesia is achievable.	3.97	0.37	4	3–5	0.0	5.3	0.671	0.860
13	I would like to have skills in learning and using artificial intelligence technologies in anesthesia.	4.13	0.53	4	3–5	0.0	21.1	0.536	0.861
14	I would like to have training on learning the use of artificial intelligence technologies in anesthesia.	4.16	0.44	4	3–5	0.0	18.4	0.653	0.858
15	I think it is necessary to include artificial intelligence technologies in the core curriculum of anesthesia education.	3.68	0.66	4	2–5	0.0	7.9	0.349	0.868

Note. N = 38. M = mean; SD = standard deviation; Mdn = median. Item wording reflects the lexically adapted (anesthesia) version administered in this study. [a]Items 1–6 (negative attitude) are printed as worded, but all item statistics are reported after reverse-scoring, so higher values indicate more favorable attitudes for every item. Floor % and Ceiling % are the proportion of respondents selecting the least favorable (1) and most favorable (5) response option, respectively. r item-total = corrected item-total correlation (item correlated with the sum of the remaining 14 items). α if deleted = Cronbach's alpha for the 15-item total scale with that item removed.

Discussion

Psychometric Evidence for ASUAITIN

This two-phase study provides the first synthesis of the ASUAITIN psychometric literature and the first application of a lexically adapted version among U.S. obstetric anesthesia providers. Overall, the published evidence generally supports the instrument's two-factor structure and acceptable internal consistency, but important gaps remain in the evidence base. Across psychometric studies, subscale reliability was consistently strong, whereas total-scale estimates were more variable and complicated by inconsistent reporting of scoring procedures. Beyond structural validity and internal consistency, little evidence is available regarding measurement error, responsiveness, hypothesis testing, or measurement invariance. In the

present sample, the lexically adapted ASUAITIN demonstrated good internal consistency comparable to values reported in nursing populations.

Evidence for structural validity was generally supportive, although important limitations remain. Both Chinese validation studies replicated the original two-factor structure, but the two confirmatory analyses fell short of conventional thresholds on different indices. Hu et al. reported CFI and TLI below 0.90 [10], and Chen et al. (2026) reported an RMSEA above 0.08 [11], so neither model met conventional criteria on all indices [38, 39]. The scoring direction behind most published total-scale coefficients cannot be determined from the reports, and where it was stated or could be read from printed values, the negative items entered the total without reversal [16, 17, 19]. Because the two subscales are oppositely keyed, scoring procedures may influence total-scale reliability estimates and complicate comparisons across studies. Nevertheless, reported reliability coefficients were generally acceptable for both the total scale and subscales across studies. Taşçı et al., who stated that no items were reverse-scored, reported a total alpha (0.830) close to both subscale alphas (0.850 and 0.835) [16]. In the present sample, where the negative items were reverse-scored, the total alpha was 0.868 and subscale alphas were 0.842 and 0.823. Taken together, these findings suggest acceptable internal consistency across studies despite differences in scoring procedures.

Existing psychometric work on ASUAITIN has adaptation across language and culture, but not across professional groups. The Turkish development study and the two Chinese validations differ from one another in language and cultural context, yet all three were conducted with clinical nurses [9–11]. Ten of the 11 applied studies share that population [12–20, 22], and the eleventh extended it only to nursing students, for whom the professional referent did not change. Whether the instrument performs comparably when the professional referent changes has not been examined. This question is distinct from cross-cultural equivalence, because several ASUAITIN items are anchored to features of nursing practice rather than to attitudes toward AI as such. Item 3 asks about harm to the nursing profession,

item 10 about routine procedures such as vital findings and pain assessment, and item 15 about the core curriculum of nursing education. Professional identity, scope of practice, procedural routine, and curricular structure differ across clinical roles, so items written around them may not carry the same meaning when the referent is changed. In the present sample, the three lowest corrected item-total correlations were for items 15 (r = 0.349), 10 (r = 0.409), and 11 (r = 0.424). Items 10 and 15 are two of the three items described above as tied to nursing practice, but item 3 did not follow the pattern (r = 0.567). With 38 respondents, this is exploratory and does not by itself indicate an item problem. The AIAS comparator reported a broader set of procedures (split-sample exploratory and confirmatory analyses, composite reliability, average variance extracted, and test-retest reliability with a confidence interval), although its report also contains values that cannot both be correct, such as an adjusted goodness-of-fit index (0.957) above the unadjusted index (0.936) [23]. No single ASUAITIN study reported all of these.

Anesthesia Application Findings

In the first application of ASUAITIN outside nursing, the lexically adapted instrument produced complete item responses, no scale-level floor or ceiling effects, and internal consistency within the range reported for nursing samples (negative attitude 0.842 and positive attitude 0.823; published subscale values 0.704 to 0.956). Total-scale alpha (0.868, 95% CI 0.768 to 0.925) is not compared with published values, because the scoring direction behind most cannot be determined. The confidence intervals are wide (the lower bound for the positive subscale was 0.700), so these estimates should be interpreted as preliminary. The lowest-scoring item concerned ethical problems arising from AI use in anesthesia practice (mean 2.89), and the highest-scoring items concerned wanting training in and skills for using AI in anesthesia (means 4.16 and 4.13). This pattern may reflect generally favorable attitudes alongside relatively greater ethical concern and an expressed need for education, although the interpretation is exploratory. Mean total scores were 2.9 points higher among CRNAs than among physician anesthesiologists, but with only eight physician anesthesiologists, this

difference cannot be interpreted. No conclusions regarding structural validity can be drawn because no factor analysis was conducted.

Limitations

This evidence synthesis is limited to published studies and therefore may not capture unpublished or ongoing validation work. All included studies were published across 2025 and 2026, which reflects both the novelty of the instrument and the early stage of this research area. Although the synthesis followed a structured, transparent search process, the limited number of studies available limits the depth of psychometric inferences. The search was limited to two databases (PubMed and Google Scholar) and to English-language articles. Seven eligible studies were identified only through forward citation searching, which indicates that database searching alone underestimates the use of instruments named mainly in methods sections. Three Chinese-language validations were excluded under the English-language criterion [33–35], so the evidence summarized here does not represent all published versions of the instrument. Two applied reports appear to draw on the same survey [14, 19], and their samples were not treated as independent. Measurement properties were categorized using the COSMIN taxonomy, but formal COSMIN risk-of-bias ratings were not assigned.

The ASUAITIN was adapted for the obstetric anesthesia provider population through lexical substitution alone. Adaptation frameworks recognize that using an instrument with a new population may require formal adaptation even without a language change [40], and the procedures omitted here, including expert committee review, content validity indexing, and pilot testing, were performed for both published English-language Chinese ASUAITIN validations [10, 11]. For context adaptations specifically, Heggestad et al. recommend comparative factor-analytic evidence and expert evaluation of content validity, neither of which was available in a sample of this size [25]. Guidance on modifying instruments for populations other than those in which they were developed remains limited [40, 41], and existing frameworks address adaptation across language, culture, and country rather than across professional role. Results

are therefore reported as descriptive characteristics of the adapted instrument in this sample and do not support inferences about ASUAITIN as validated in nursing populations.

The anesthesia-provider sample was a convenience sample of providers who agreed to take part in an interview study about AI and clinical risk reasoning, and these providers may hold more favorable or more considered views of AI than the broader workforce. Physician anesthesiologists were few (n = 8), the instrument was administered once, so test-retest reliability could not be assessed, and no comparison measure was administered to support hypotheses testing.

Next Steps for ASUAITIN

The current evidence for ASUAITIN includes consistent subscale reliability and a two-factor structure in nursing samples, along with a first descriptive indication that the lexically adapted instrument yields internally consistent scores among obstetric anesthesia providers. Several gaps remain. First, formal adaptation for anesthesia providers, including expert committee review, cognitive interviewing, and content validity indexing, should precede further use, with particular attention to items anchored to nursing practice. Second, adequately powered confirmatory factor analysis should test the two-factor structure in anesthesia providers and model the wording effect raised by Chen et al. (2026) [11], and reports should state which published version was used and how the negative items were scored. Third, measurement invariance should be tested across professions, particularly between CRNAs and physician anesthesiologists, and across practice settings. Fourth, hypotheses testing for construct validity should use prespecified hypotheses about the direction and magnitude of expected relationships. Fifth, test-retest reliability and measurement error should be established, since only two included studies have assessed temporal stability, and none has reported measurement error. Finally, longitudinal designs should evaluate responsiveness, which no published study has assessed.

Until that work is done, ASUAITIN scores among anesthesia providers are best used descriptively, for example, to identify training needs, which respondents in this sample rated highly, or to inform readiness for AI implementation.

Conclusions

ASUAITIN is now used in Turkish and Chinese nursing research, but its psychometric record remains limited. Existing studies provide evidence of acceptable to excellent total and subscale internal consistency and a replicated two-factor structure, although neither validation study's confirmatory factor analysis met conventional thresholds across all fit indices, and substantial psychometric work remains to be completed. Validation across professions is the step that would show whether the instrument can be used beyond nursing. The first application of ASUAITIN outside nursing, in a sample of U.S. obstetric anesthesia providers, produced subscale internal consistency within the range of the nursing samples reviewed here. This finding is descriptive: internal consistency alone cannot show that the construct is equivalent across professional groups, and the finding rests on a lexically adapted instrument administered in a small sample. Formal adaptation and validation in an adequately powered study are therefore needed before use beyond exploratory applications.

608 **Abbreviations**

AI	Artificial Intelligence
AIAS	*Artificial Intelligence Attitude Scale for Nurses*
ASUAITIN	*Attitude Scale Toward the Use of Artificial Intelligence Technologies in Nursing*
CFI	Comparative Fit Index
CI	Confidence Interval
COSMIN	*COnsensus-based Standards for the selection of health Measurement INstruments*
CRNA	Certified Registered Nurse Anesthetist
GFI	Goodness-of-fit index
ICC	Intraclass Correlation Coefficient
IRB	Institutional Review Board
r	Pearson correlation coefficient
REDCap	Research Electronic Data Capture
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
TLI	Tucker–Lewis Index
α (Cronbach's Alpha)	Internal consistency reliability coefficient

609

Declarations

Ethics Approval and Consent to Participate

This study was conducted in accordance with the Declaration of Helsinki and the U.S. Federal Policy for the Protection of Human Subjects (45 CFR 46). The Emory University Institutional Review Board reviewed the study and determined it exempt under 45 CFR 46.104(d)(2)(ii) and (4) (STUDY00009239). All participants provided electronic informed consent before participation. Phase 1 used only published literature and did not involve human participants.

Consent for Publication

Not applicable.

Availability of Data and Materials

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contributions

Conceptualization: SW (main), SG (supporting); Methodology: SW (main), SG (supporting); Data collection: SW (main), PK (supporting); Data curation: SW (main), PK (supporting); Formal analysis: SW (main), PK (supporting); Writing (original draft): SW (main), PK (supporting);

Writing (review & editing): SG (main), SW (supporting), PK (supporting); Supervision: SW. All authors read and approved the final manuscript.

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