

Antecedents of Adoption Intention for AI-Driven Wearable Technology in Malaysian Healthcare: A Pilot Study Using Partial Least Squares Structural Equation Modeling

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Abstract

This study reports the pilot phase of a larger doctoral investigation into the adoption of AI-driven wearable technology in Malaysian healthcare. Guided by an integration of Diffusion of Innovations theory and the Technology Acceptance Model, the pilot tested seven direct effect hypotheses linking compatibility, relative advantage, trialability, complexity, observability, perceived ease of use, and perceived usefulness to adoption intention. Data were collected from healthcare sector respondents at a professional conference in Kuala Lumpur in August 2026 (N = 93, after removing two duplicates from 95 raw responses). Partial least squares structural equation modeling was used for its suitability to prediction oriented research. The structural model explained 60.0 percent of the variance in adoption intention. Perceived usefulness (beta = 0.261), perceived ease of use (beta = 0.201), observability (beta = 0.174), compatibility (beta = 0.162), and complexity (beta = -0.152) significantly predicted adoption intention (all $p < .05$); relative advantage and trialability did not. Composite reliability exceeded 0.78 for all nine constructs, and heterotrait monotrait ratios for all 36 construct pairs fell below the conservative 0.85 threshold as point estimates, but bootstrap confidence intervals crossed 0.85 for six of the eight adoption intention pairs, so discriminant validity for that construct remains provisional. Perceived regulatory support was retained for reliability assessment but not tested as a moderator here, a test reserved for the full study. Findings offer preliminary support for the framework and considerations for the full scale study.

Keywords: *AI-driven wearable technology; diffusion of innovations; technology acceptance model; partial least squares structural equation modeling; pilot study; Malaysian healthcare; SDG 3 (Good Health and Well-being).*

1. Introduction

Wearable devices that use artificial intelligence to collect, interpret, and act on health-related data, such as smartwatches, fitness trackers, and connected health monitors, are increasingly positioned as tools for continuous, participatory healthcare. Their promise rests on shifting care from episodic clinical encounters toward ongoing monitoring that can support earlier detection and more informed self-management (Nezamdoust et al., 2022; Gao et al., 2015). Global evidence across smartwatch, fitness tracker, and general wearable contexts consistently identifies usefulness, ease of use, and visibility of benefits as central to whether such devices are adopted (Kim & Shin, 2015; Chuah et al., 2016; Talukder

et al., 2019), while healthcare specific studies add that privacy calculus and institutional trust shape adoption further once the device is framed as a health tool rather than a consumer gadget (Li et al., 2016).

1.1 Background of Study

In Malaysia, the shift toward AI-driven health technology is unfolding alongside an evolving regulatory environment. The Medical Device Authority, established under the Medical Device Act 2012 and the Medical Device Authority Act 2012, oversees the safety and market authorization of medical devices, and has introduced a regulatory sandbox intended to allow AI-driven medical technologies to be trialled under supervised, real world conditions (Medical Device Authority, 2025). This sits within a broader wave of Malaysian digital health research: recent systematic and empirical work has examined eHealth adoption barriers among patients and healthcare professionals (Sampa et al., 2025), telemedicine adoption among physicians, and AI-driven telemedicine adoption among knowledge workers using Partial Least Squares Structural Equation Modelling (Naji et al., 2025), as well as AI adoption more broadly among Malaysian organizations (Enshassi et al., 2025). AI-driven wearable technology specifically, as distinct from telemedicine or general eHealth platforms, has not yet been examined through this combined lens in the Malaysian healthcare context, which motivates the present study.

1.2 Problem Statement

Despite this momentum, adoption of AI-driven wearable technology among healthcare stakeholders in Malaysia remains uneven. Prior technology adoption research points to a combination of technological, socioeconomic, regulatory, and cultural behavioral barriers that jointly shape whether an individual forms an intention to adopt a new health technology (Rogers, 2003; Davis, 1989; Venkatesh et al., 2003). Understanding how these factors operate specifically among Malaysian healthcare professionals, administrators, support staff, students, and members of the public who interact with the healthcare system is the underlying purpose of the doctoral study from which this pilot is drawn. Before that full scale study is undertaken, however, the measurement instrument and the plausibility of its hypothesized relationships require preliminary testing, which is the specific problem this pilot study addresses.

1.3 Research Gap

Prior technology adoption research in the Malaysian healthcare context has examined eHealth adoption barriers among patients and healthcare professionals (Sampa et al., 2025), telemedicine and AI-driven telemedicine adoption (Naji et al., 2025), and AI adoption more broadly among Malaysian organizations (Enshassi et al., 2025). Outside Malaysia, wearable specific research has established relative advantage, visibility, and usefulness as central predictors of smartwatch and fitness tracker adoption (Kim & Shin, 2015; Chuah et al., 2016; Talukder et al., 2019) and has extended the Technology Acceptance Model to healthcare wearable devices specifically (Gao et al., 2015; Li et al., 2016). As Table 1 summarizes, however, no identified study has combined Diffusion of Innovations theory and the Technology Acceptance Model to examine AI-driven wearable technology, specifically, within the Malaysian healthcare context, nor tested perceived regulatory support as a moderator of this combined framework in a healthcare setting; the only comparable use of perceived regulatory support as a moderator identified in the adoption literature is in the financial technology sector (Amnas et al., 2024). This combination of technology, theoretical integration, moderating mechanism, and national regulatory context constitutes the specific gap this doctoral study, and the present pilot, is designed to address.

1.4 Research Aim and Objectives

This pilot study serves two purposes consistent with standard pilot study practice (Hertzog, 2008): to obtain a preliminary, indicative test of the direct effect hypotheses linking Diffusion of Innovations and Technology Acceptance Model constructs to adoption intention, and to evaluate the psychometric behavior of the measurement instrument before problems propagate into a full scale study.

Research Aim: The aim of this pilot study is to provide a preliminary, indicative test of the direct relationships between Diffusion of Innovations and Technology Acceptance Model constructs and

adoption intention for AI-driven wearable technology among Malaysian healthcare sector respondents, and to evaluate the psychometric adequacy of the measurement instrument before it is deployed at full scale.

Research Objectives:

RO1: To test the direct effect of compatibility, relative advantage, trialability, complexity, observability, perceived ease of use, and perceived usefulness on adoption intention for AI-driven wearable technology, at pilot scale.

RO2: To assess, through indicator loadings, reliability, and discriminant validity criteria, the psychometric performance of the measurement instrument and identify refinements needed before full scale data collection.

Perceived regulatory support, theorized in the parent study as a moderator of every direct relationship, is included here only for measurement level reliability assessment; testing it as a moderator requires substantially more statistical power than this 93-respondent pilot can provide and is deferred to the full study. Accordingly, this study addresses two research questions:

RQ1: To what extent do compatibility, relative advantage, trialability, complexity, observability, perceived ease of use, and perceived usefulness individually predict adoption intention for AI-driven wearable technology among Malaysian healthcare sector respondents, at pilot scale?

RQ2: What does pilot stage measurement model assessment reveal about the instrument that should inform its refinement before full scale data collection?

2. Literature Review and Hypotheses

2.1 Diffusion of Innovations Theory

Rogers (2003) proposed that the rate at which an innovation is adopted depends on five perceived characteristics: relative advantage, compatibility, complexity, trialability, and observability. Moore and Benbasat (1991) operationalized these characteristics for information technology contexts, producing refined measures that have since been widely applied to the adoption of digital tools, including health technologies. Applied to AI-driven wearable technology, compatibility captures the degree to which the technology fits an individual's existing routines and health management practices; relative advantage captures the perceived superiority of the wearable technology over conventional methods of accessing health information; trialability captures the opportunity to experiment with the technology before committing to it; complexity captures the perceived difficulty of understanding and using the technology; and observability captures the visibility of the technology's benefits, both to the user directly and through the observed use of others. In wearable specific research, relative advantage and visibility of use by others have repeatedly emerged as strong predictors of smartwatch and fitness tracker adoption (Kim & Shin, 2015; Chuah et al., 2016), while compatibility with existing habits and routines has been found to shape both initial adoption and the intention to recommend the technology onward (Talukder et al., 2019).

2.2 Technology Acceptance Model

Davis (1989) proposed that perceived usefulness and perceived ease of use are the two fundamental determinants of an individual's acceptance of information technology, with perceived usefulness reflecting the degree to which a person believes that using a system would enhance their performance, and perceived ease of use reflecting the degree to which a person believes that using it would be free of effort. Both constructs have repeatedly been applied to health technology adoption, including mobile health applications used by nurses, where perceived usefulness and ease of use meaningfully shaped adoption behavior alongside organizational and technical factors (Nezamdoust et al., 2022), and wearable healthcare devices specifically, where perceived usefulness has been shown to interact with privacy calculus judgments in shaping adoption intention (Li et al., 2016; Gao et al., 2015). The Unified Theory

of Acceptance and Use of Technology extends the Technology Acceptance Model with performance expectancy, effort expectancy, social influence, and facilitating conditions, and has likewise been applied successfully to health technology contexts (Venkatesh et al., 2003); the present study retains the narrower Technology Acceptance Model and Diffusion of Innovations combination for consistency with the parent dissertation's framework.

2.3 Perceived Regulatory Support

Beyond the individual level perceptions captured by Diffusion of Innovations theory and the Technology Acceptance Model, adoption of a health technology also depends on the institutional environment in which that technology is used. A recent scoping review of artificial intelligence adoption across healthcare settings identified regulatory and legal frameworks as a recurring, cross cutting facilitator or barrier, alongside trust, governance structure, and transparency (Hassan et al., 2024). Perceived regulatory support, defined here as an individual's confidence that relevant authorities provide adequate oversight, safety standards, and enforcement for AI-driven wearable healthcare technology, is theorized in the parent study as a moderator of the seven relationships above, strengthening them when regulatory confidence is high. This mirrors recent evidence from an adjacent technology adoption context, where perceived regulatory support was shown to moderate a technology adoption relationship in the financial technology sector (Amnas et al., 2024). Because testing an interaction effect requires substantially more statistical power than testing a direct effect, perceived regulatory support is retained in the present pilot only as a measured construct for reliability assessment, and its moderating role is reserved for the full scale study.

2.4 Summary of Prior Studies and Positioning of the Present Study

Table 1 situates the present pilot relative to closely related adoption studies identified in the preceding review, summarizing each study's technological focus, theoretical framework, method, and principal findings. The comparison makes explicit the specific combination this study contributes: an integration of Diffusion of Innovations theory and the Technology Acceptance Model, applied to AI-driven wearable technology specifically, within the Malaysian healthcare sector, with perceived regulatory support theorized as a moderating mechanism not previously tested for this technology and framework combination in a healthcare setting.

Table 1. Summary of Prior Studies and Positioning of the Present Study

Study	Context	Framework	Method	Key Findings	Gap vs. Present Study
Kim & Shin (2015)	Smartwatches (consumer, South Korea)	Extended Technology Acceptance Model	Survey, SEM	Relative advantage and visibility of use strongly predict smartwatch adoption	Consumer, non-healthcare context; no DOI-TAM integration or regulatory moderator
Chuah et al. (2016)	Smartwatches (consumer wearables)	UTAUT-based wearable adoption model	Survey	Usefulness and visibility drive smartwatch adoption	Consumer market; no healthcare setting or regulatory construct
Talukder et al. (2019)	Fitness wearables	Integrated technology adoption model	Survey	Compatibility shapes adoption and intention to recommend	Fitness/consumer focus; not healthcare specific; no DOI-TAM-PRS integration
Gao et al. (2015); Li et al. (2016)	Healthcare wearable devices (China)	Technology Acceptance Model; privacy calculus	Empirical survey	Usefulness and ease of use shape adoption; interacts with privacy calculus	Healthcare wearables addressed, but outside Malaysia; DOI constructs and regulatory support not modeled
Nezamdoust et al. (2022)	Mobile health application (nurses)	Determinant factor model	Empirical study	Usefulness and ease of use shape adoption alongside	Mobile health app for nurses, not wearables; not Malaysia; no DOI or regulatory construct

				organizational/technical factors	
Naji et al. (2025)	AI-driven telemedicine (Malaysia)	Adoption model (unspecified)	PLS-SEM	Identifies factors shaping knowledge workers' telemedicine adoption intention	Malaysian and PLS-SEM based, but telemedicine rather than wearable technology
Sampa et al. (2025)	eHealth adoption (Malaysia)	Not applicable (review)	Systematic review	Synthesizes barriers to eHealth adoption among patients and professionals	Review, not empirical; eHealth broadly, not wearables specifically
Enshassi et al. (2025)	AI adoption for digital marketing (Malaysian SMEs)	Adoption barriers/drivers framework	Empirical study	Identifies drivers and barriers of AI adoption	Non-healthcare sector; different technology and outcome variable
Amnas et al. (2024)	Financial technology adoption	Technology adoption model with regulatory moderator	Survey, PLS-SEM	Perceived regulatory support moderates a technology adoption relationship	Demonstrates PRS as a moderator, but in financial technology, not healthcare or wearables
Present study	AI-driven wearable technology (Malaysian healthcare)	Diffusion of Innovations + Technology Acceptance Model, with perceived regulatory support as moderator	PLS-SEM (pilot, N = 93)	Preliminary support for five of seven direct effects; instrument validated for full scale deployment	Addresses the combined gap identified above

2.5 Hypothesis Development

Consistent with Diffusion of Innovations theory and the Technology Acceptance Model, and with prior applications of both frameworks to health technology and wearable device contexts (Gao et al., 2015; Kim & Shin, 2015; Talukder et al., 2019), the following seven direct effect hypotheses were tested in this pilot.

H1: Compatibility has a positive effect on adoption intention.

H2: Relative advantage has a positive effect on adoption intention.

H3: Trialability has a positive effect on adoption intention.

H4: Complexity has a negative effect on adoption intention.

H5: Observability has a positive effect on adoption intention.

H6: Perceived ease of use has a positive effect on adoption intention.

H7: Perceived usefulness has a positive effect on adoption intention.

3. Methodology

3.1 Research Design

This study used a cross sectional, quantitative survey design and reports the pilot phase of a larger doctoral study. Consistent with the purpose of pilot testing (Hertzog, 2008), the objective was not to confirm the full theoretical model but to obtain an indicative, preliminary test of the seven direct effect hypotheses and to evaluate how the measurement instrument performs before it is deployed at full scale. Figure 1

summarizes the step-by-step procedure followed, from population definition through pilot stage interpretation.

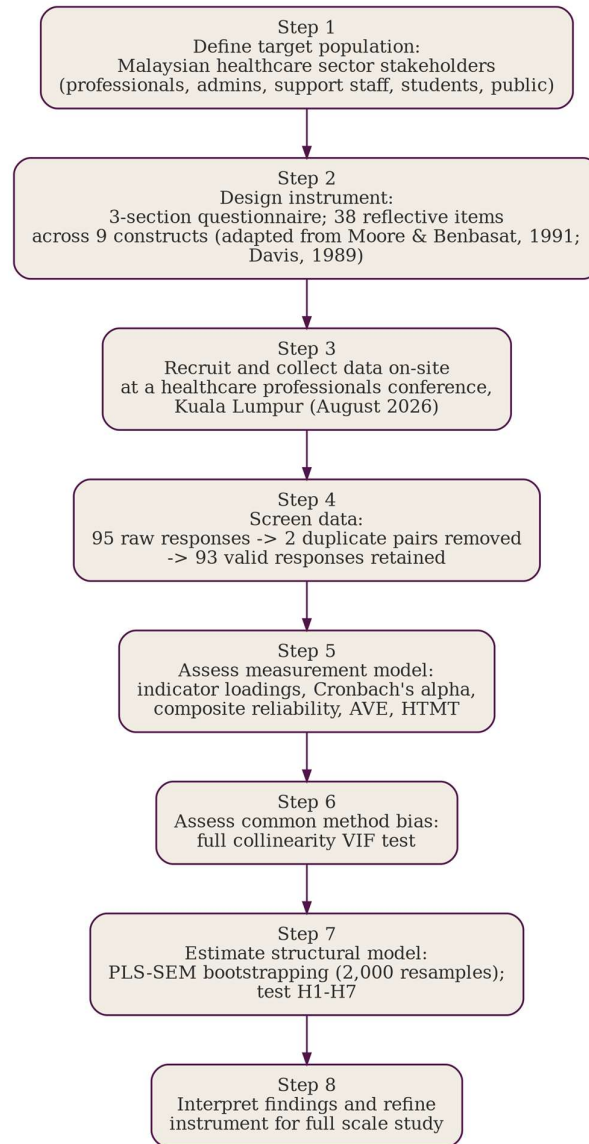


Figure 1. Step-by-Step Methodological Procedure.

3.2 Population and Sample

A target population comprised individuals working, studying, or otherwise involved in the Malaysian healthcare sector, including healthcare professionals, administrators, support staff, students, and members of the public with healthcare exposure. General public users with healthcare exposure were also included because conference attendees included caregivers and patient representatives alongside healthcare professionals, all of whom interact directly with the healthcare system and were considered part of the applied target population for this technology. Respondents were recruited on site at a healthcare professionals conference held in Kuala Lumpur, Malaysia, in August 2026, using an online form completed by attendees; this venue-based approach was chosen specifically to reach concentrated numbers of the target population, healthcare sector stakeholders, in a single, efficient data collection window. Of the more than 250 attendees at the conference, 95 completed the questionnaire, an estimated response rate under 38 percent. During data screening, two pairs of responses were found to be identical across all 38 Likert items and all eight demographic items, submitted 15 minutes apart in one case and approximately two hours and forty-eight minutes apart in the other, both from respondents sharing the

same age and gender profile; given the extremely low probability of two independent respondents matching by chance across 46 categorical fields, the later entry in each pair was treated as a duplicate submission and removed, leaving 93 responses for analysis. The final sample was 57.0 percent female and 43.0 percent male, spanned five age bands with the largest concentration (43.0 percent) in the 26 to 33 range, and included healthcare professionals (24.7 percent), healthcare students or trainees (22.6 percent), healthcare support staff (21.5 percent), general public users with healthcare exposure (18.3 percent), and healthcare administrators or managers (12.9 percent). Full demographic detail is reported in Table 2. The first 51 responses received were screened as an interim check during data collection and had identified a discriminant validity concern involving perceived usefulness, observability, and adoption intention; data collection continued to the present sample of 93 specifically to evaluate whether this concern persisted at a larger sample size, and this comparison is referenced in Section 5.1.

3.3 Instrument

The questionnaire comprised three sections. Section A screened respondents for involvement in the healthcare sector and familiarity with AI-driven wearable technology. Section B measured nine constructs using 38 reflective items on a five point scale ranging from 1 (strongly disagree) to 5 (strongly agree): perceived usefulness (5 items), perceived ease of use (5 items), compatibility (4 items), perceived complexity (3 items), observability (3 items), trialability (5 items), relative advantage (4 items), perceived regulatory support (5 items), and adoption intention (4 items). Perceived complexity items were worded so that higher scores indicate greater perceived complexity and were retained in this direction, consistent with the hypothesized negative effect on adoption intention, rather than reverse coded. Section C collected respondent background information, including age, gender, education, healthcare related role, years of healthcare experience, organization type, prior experience with AI-driven wearable technology, and familiarity with AI applications in healthcare.

3.4 Data Analysis

Partial least squares structural equation modeling was used to estimate both the measurement model and the structural model. This approach was selected for its established suitability for prediction oriented, theory refining research, where it places fewer distributional demands on the data than covariance based structural equation modeling while still allowing simultaneous estimation of multiple relationships (Chin, 1998; Hair et al., 2019). The measurement model was assessed using indicator loadings, Cronbach's alpha (Cronbach, 1951; Nunnally, 1978), composite reliability, and average variance extracted; discriminant validity was assessed using the heterotrait monotrait ratio of correlations, which has been shown to detect discriminant validity problems more reliably than the classical Fornell and Larcker criterion (Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was estimated using a standard partial least squares path modeling algorithm with reflective, mode A outer estimation and the path weighting inner estimation scheme; statistical significance of path coefficients was assessed using bootstrapping with 2,000 resamples, from which standard errors, t values, two tailed p values, and 95 percent percentile confidence intervals were derived. Common method bias was assessed using a full collinearity variance inflation factor test, in which each construct's latent variable score was regressed on the scores of all remaining constructs; variance inflation factors below the conservative threshold of 3.3 indicate that common method bias is unlikely to be a serious concern (Kock, 2015). All analyses were conducted using SmartPLS 4.

Consistent with its role as a pilot, the structural model tested in this study includes only the seven hypothesized direct effects (H1 to H7). Perceived regulatory support is reported descriptively and included in the measurement model reliability and discriminant validity assessment, but it is not tested as a moderator here; with seven predictor constructs and eight proposed moderation paths, the full theoretical model requires a substantially larger sample than 93 respondents to achieve adequate statistical power for interaction effects specifically, and this test is deferred to the full dissertation study. Findings reported below should accordingly be read as preliminary and indicative of the direct effect structure rather than as a confirmatory test of the complete moderated model.

4. Results

4.1 Respondent Profile

Table 2 summarizes the demographic characteristics of the 93 respondents retained after data screening.

Table 2. Respondent Profile (N = 93).

Category	Group	n	%
Age	18 to 25	16	17.2%
	26 to 33	40	43.0%
	34 to 42	16	17.2%
	43 to 50	14	15.1%
	50+	7	7.5%
Gender	Male	40	43.0%
	Female	53	57.0%
Education	Secondary School	11	11.8%
	Diploma	16	17.2%
	Bachelor's degree	47	50.5%
	Master's degree	16	17.2%
	Doctorate (PhD)	3	3.2%
Healthcare Role	Healthcare professional	23	24.7%
	Healthcare student/trainee	21	22.6%
	Healthcare support staff	20	21.5%
	General public user	17	18.3%
	Healthcare administrator/manager	12	12.9%
Experience	Less than 1 year	27	29.0%
	1 to 5 years	34	36.6%
	6 to 10 years	14	15.1%
	11 to 15 years	6	6.5%
	More than 15 years	12	12.9%
Organization	Public healthcare organization	35	37.6%
	Private healthcare organization	21	22.6%
	University/teaching hospital	21	22.6%
	Clinic/primary care	16	17.2%
Prior Wearable Use	Never used	14	15.1%
	Used once or twice	25	26.9%
	Occasional user	34	36.6%
	Regular user	20	21.5%
AI Familiarity	Not at all familiar	12	12.9%
	Slightly familiar	20	21.5%
	Moderately familiar	31	33.3%
	Very familiar	18	19.4%
	Extremely familiar	12	12.9%

4.2 Common Method Bias Assessment

Before evaluating the measurement and structural models, common method bias was assessed using a full collinearity variance inflation factor test (Kock, 2015), in which each construct's latent variable score was regressed on the scores of all remaining constructs. As shown in Table 3, the range all variance inflation factors was 1.336 to 2.783, comfortably below the conservative threshold of 3.3. This indicates that common method bias is unlikely to be a serious concern in this dataset, providing reasonable confidence that the relationships reported below are not substantially inflated by shared method variance. This full collinearity test is a common method bias diagnostic in which every construct, including adoption intention, is regressed on all others simultaneously; it is conceptually distinct from, and does not substitute for, the structural (inner) model collinearity assessment among the seven predictor constructs specifically in their joint regression on adoption intention (Hair et al., 2019). That inner model assessment is reported in Section 4.5.

Table 3. Full Collinearity Variance Inflation Factor (VIF) Test.

Construct	R-squared	VIF
Perceived Usefulness (PU)	0.471	1.889
Perceived Ease of Use (PEOU)	0.347	1.532
Compatibility (COM)	0.325	1.480
Perceived Complexity (CPLX)	0.368	1.582
Observability (OBS)	0.311	1.452
Trialability (TRI)	0.252	1.336
Relative Advantage (RA)	0.329	1.490
Perceived Regulatory Support (PRS)	0.318	1.467
Adoption Intention (AIU)	0.641	2.783

4.3 Measurement Model Assessment

Table 4 reports indicator loading ranges, Cronbach's alpha, composite reliability, and average variance extracted for all nine constructs. Composite reliability exceeded the conventional 0.70 threshold for every construct, ranging from 0.780 (observability) to 0.836 (perceived usefulness). Cronbach's alpha ranged from 0.611 (observability) to 0.755 (perceived usefulness); adoption intention's alpha (0.690) sits just below the conventional 0.70 benchmark but its composite reliability (0.813) is comfortably above it, a divergence that is expected given composite reliability weights items by their estimated loadings while Cronbach's alpha assumes all items contribute equally.

Average variance extracted exceeded the conventional 0.50 threshold for six of the nine constructs: perceived usefulness (0.508), compatibility (0.544), perceived complexity (0.615), observability (0.551), perceived regulatory support (0.503), and adoption intention (0.521). Perceived ease of use (0.493), trialability (0.474), and relative advantage (0.492) fell only marginally below the threshold; given that composite reliability for all three constructs exceeds 0.79, this shortfall is unlikely to materially affect convergent validity conclusions (Fornell & Larcker, 1981). At the level of individual indicators, the weakest loading (one observability item at 0.541) remains above the minimum acceptable range for exploratory work.

Table 4. Measurement Model Summary.

Construct	Items	Loading Range	Alpha	CR	AVE
Perceived Usefulness (PU)	5	0.614 to 0.812	0.755	0.836	0.508
Perceived Ease of Use (PEOU)	5	0.652 to 0.737	0.742	0.829	0.493
Compatibility (COM)	4	0.637 to 0.797	0.725	0.826	0.544
Perceived Complexity (CPLX)	3	0.761 to 0.820	0.688	0.827	0.615
Observability (OBS)	3	0.541 to 0.872	0.611	0.780	0.551
Trialability (TRI)	5	0.593 to 0.773	0.722	0.817	0.474
Relative Advantage (RA)	4	0.604 to 0.795	0.650	0.793	0.492
Perceived Regulatory Support (PRS)	5	0.616 to 0.769 (not in structural model)	0.749	0.834	0.503
Adoption Intention (AIU)	4	0.678 to 0.764	0.690	0.813	0.521

4.4 Discriminant Validity

Table 5 reports the complete heterotrait monotrait ratio matrix for all 36 pairs among the nine constructs, including adoption intention. Every pair fell below the conservative 0.85 threshold (Henseler et al., 2015). Perceived usefulness and adoption intention showed the highest ratio (0.829), followed by perceived complexity and adoption intention (0.747); both values are close enough to the threshold that a point estimate alone is not, by itself, decisive evidence of discriminant validity. Table 6 accordingly reports the 95 percent bootstrap confidence interval for each ratio; a ratio whose upper confidence bound

remains below 0.85 provides materially stronger support for discriminant validity than the point estimate in isolation (Henseler et al., 2015).

Six of the eight construct pairs involving adoption intention show a bootstrap upper confidence bound above 0.85 (Table 6), so the discriminant validity picture is more cautious than the point estimates alone suggest; see Section 5.1 for the revised interpretation.

Table 5. Heterotrait-Monotrait Ratio (HTMT) Matrix, Including Adoption Intention (AIU)

	PU	PEOU	COM	CPLX	OBS	TRI	RA	PRS	AIU
PU	-	0.565	0.491	0.629	0.597	0.499	0.590	0.312	0.829
PEOU		-	0.536	0.413	0.499	0.493	0.298	0.276	0.737
COM			-	0.541	0.326	0.480	0.427	0.455	0.664
CPLX				-	0.474	0.483	0.615	0.537	0.747
OBS					-	0.407	0.549	0.392	0.712
TRI						-	0.398	0.271	0.551
RA							-	0.512	0.677
PRS								-	0.676
AIU	0.829	0.737	0.664	0.747	0.712	0.551	0.677	0.676	-

Table 6. HTMT Bootstrap 95% Confidence Intervals (2,000 Resamples)

Construct Pair	HTMT	95% CI Lower	95% CI Upper
PU - PEOU	0.565	0.432	0.754
PU - COM	0.491	0.351	0.704
PU - CPLX	0.629	0.397	0.839
PU - OBS	0.597	0.418	0.845
PU - TRI	0.499	0.368	0.722
PU - RA	0.590	0.436	0.819
PU - PRS	0.312	0.235	0.529
PU - AIU	0.829	0.661	0.997
PEOU - COM	0.536	0.370	0.759
PEOU - CPLX	0.413	0.263	0.636
PEOU - OBS	0.499	0.292	0.782
PEOU - TRI	0.493	0.337	0.766
PEOU - RA	0.298	0.234	0.556
PEOU - PRS	0.276	0.228	0.525
PEOU - AIU	0.737	0.556	0.919
COM - CPLX	0.541	0.346	0.759
COM - OBS	0.326	0.202	0.639
COM - TRI	0.480	0.310	0.715
COM - RA	0.427	0.287	0.693
COM - PRS	0.455	0.320	0.663
COM - AIU	0.664	0.487	0.858
CPLX - OBS	0.474	0.248	0.765
CPLX - TRI	0.483	0.315	0.726
CPLX - RA	0.615	0.437	0.873
CPLX - PRS	0.537	0.374	0.730
CPLX - AIU	0.747	0.574	0.933
OBS - TRI	0.407	0.300	0.743
OBS - RA	0.549	0.379	0.829

OBS - PRS	0.392	0.231	0.655
OBS - AIU	0.712	0.526	0.928
TRI - RA	0.398	0.256	0.720
TRI - PRS	0.271	0.237	0.514
TRI - AIU	0.551	0.397	0.771
RA - PRS	0.512	0.346	0.758
RA - AIU	0.677	0.477	0.898
PRS - AIU	0.676	0.500	0.861

4.5 Structural Model and Hypothesis Testing

The structural model explained 60.0 percent of the variance in adoption intention (R-squared = 0.600; bootstrap mean = 0.649, SD = 0.049). Table 7 reports the standardized path coefficients, bootstrap standard errors, t values, p values, and 95 percent confidence intervals for each hypothesized path, and Figure 2 presents the corresponding path diagram. Perceived usefulness (H7, beta = 0.261, p = .003), perceived ease of use (H6, beta = 0.201, p = .007), observability (H5, beta = 0.174, p = .021), compatibility (H1, beta = 0.162, p = .024), and complexity (H4, beta = -0.152, p = .027) were statistically significant predictors of adoption intention at the conventional 0.05 level, with complexity's negative sign matching its hypothesized direction. Relative advantage (H2, p = .123) and trialability (H3, p = .508) did not reach significance. Five of the seven hypothesized direct effects are therefore supported at this sample size, compared with two of seven at the earlier pilot sample of 51 respondents; every path coefficient across both samples remained directionally consistent with its hypothesis.

Table 7. Structural Model Results (Bootstrap, 2,000 Resamples).

Hyp.	Path	Beta	SE	t	p	95% CI	Decision
H1	COM -> AIU	0.162	0.072	2.251	.024	[0.024, 0.306]	Supported
H2	RA -> AIU	0.125	0.081	1.542	.123	[-0.030, 0.277]	Not supported
H3	TRI -> AIU	0.056	0.085	0.662	.508	[-0.103, 0.230]	Not supported
H4	CPLX -> AIU	-0.152	0.068	-2.217	.027	[-0.278, -0.014]	Supported
H5	OBS -> AIU	0.174	0.075	2.316	.021	[0.029, 0.326]	Supported
H6	PEOU -> AIU	0.201	0.075	2.691	.007	[0.048, 0.340]	Supported
H7	PU -> AIU	0.261	0.087	2.992	.003	[0.098, 0.440]	Supported

Perceived usefulness (H7, beta = 0.261, p = .003), perceived ease of use (H6, beta = 0.201, p = .007), observability (H5, beta = 0.174, p = .021), compatibility (H1, beta = 0.162, p = .024), and complexity (H4, beta = -0.152, p = .027) were statistically significant predictors of adoption intention at the conventional 0.05 level, with complexity's negative sign matching its hypothesized direction. Relative advantage (H2, p = .123) and trialability (H3, p = .508) did not reach significance. Five of the seven hypothesized direct effects are therefore supported at this sample size, compared with two of seven at the earlier pilot sample of 51 respondents; every path coefficient across both samples remained directionally consistent with its hypothesis.

Inner model variance inflation factors, which assess collinearity among the seven predictor constructs specifically in their joint regression on adoption intention, ranged from 1.30 to 1.60, comfortably below the conservative 3.3 threshold recommended by Hair et al. (2019); this indicates that the path coefficients above are not materially distorted by collinearity among the predictor constructs themselves, a check that is conceptually distinct from the full collinearity common method bias test reported in Section 4.2.

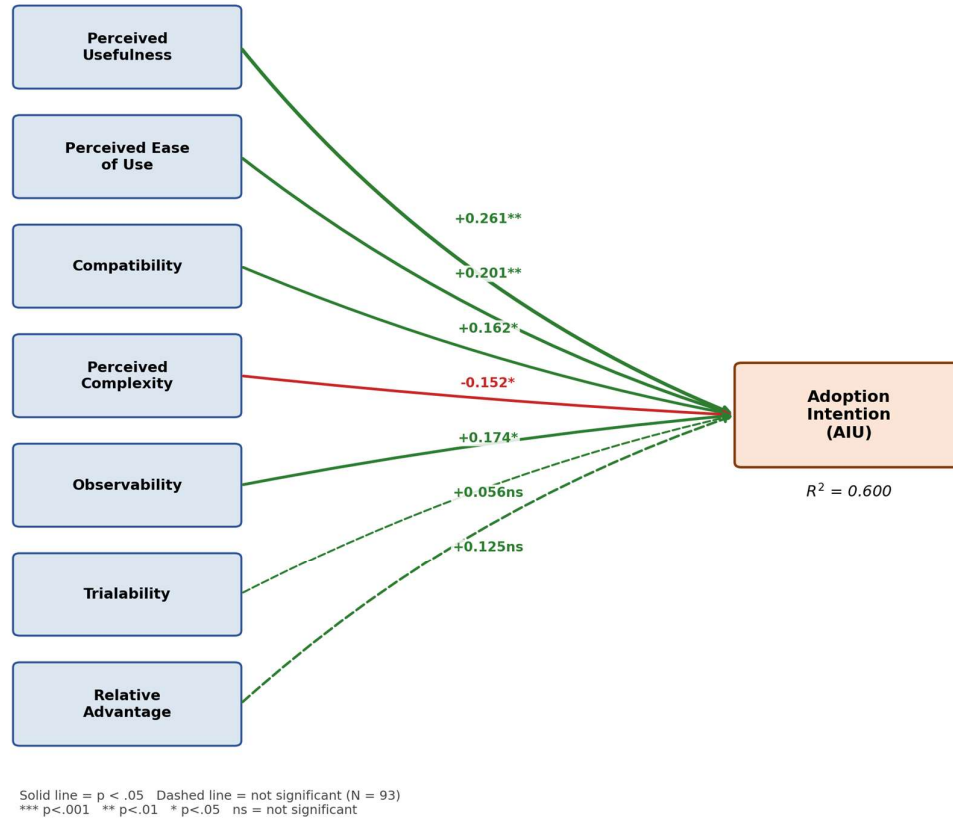


Figure 2. Structural Model Path Diagram. Solid lines indicate $p < .05$; dashed lines indicate paths not significant. *** $p < .001$, ** $p < .01$, * $p < .05$.

5. Discussion

5.1 Interpretation of Findings

This study provides preliminary support for the proposed integration of Diffusion of Innovations theory and the Technology Acceptance Model in explaining adoption intention for AI-driven wearable technology among Malaysian healthcare sector respondents, with five of seven hypothesized direct effects reaching significance. The significant effects of perceived usefulness (H7) and perceived ease of use (H6) replicate the two central relationships of the Technology Acceptance Model in this new technology and population context (Davis, 1989), and are consistent with prior findings that usefulness and ease of use shape adoption of healthcare specific wearable and mobile health technologies (Nezamdoust et al., 2022; Li et al., 2016; Gao et al., 2015). The significant effect of compatibility (H1) is consistent with the broader Diffusion of Innovations finding that an innovation's fit with existing routines is often among its strongest predictors of adoption (Rogers, 2003; Talukder et al., 2019), while the significant effect of observability (H5) aligns with evidence that the visibility of an innovation's benefits, directly and through observing others, drives adoption, particularly in smartwatch and wearable contexts (Kim & Shin, 2015; Chuah et al., 2016). The significant, negative effect of complexity (H4) confirms that perceived difficulty of use meaningfully suppresses adoption intention in this sample, consistent with its hypothesized role as a barrier.

Relative advantage (H2) did not reach significance, but its coefficient and standard error (beta = 0.125, SE = 0.081) imply that conventional significance would plausibly be reached at a sample of approximately 200 respondents, well within the range planned for the full study; at this pilot's sample size, insufficient statistical power remains a live, and arguably primary, explanation for this null result. Trialability (H3), by contrast, showed a coefficient close to zero (beta = 0.056, SE = 0.085), the smallest in the model,

and on the same reasoning would not plausibly reach significance even at a sample on the order of 300 respondents; power alone is therefore a less satisfying explanation for trialability specifically. One plausible substantive explanation for trialability's near-zero effect is that, for healthcare professionals attending a conference on emerging health technology, the ability to try a device before adopting it may already be assumed or taken for granted, leaving comparatively little variance for this construct to explain once usefulness, ease of use, compatibility, observability, and complexity are accounted for. This interpretation is offered cautiously and should be tested directly in the full study, ideally with a sample that also captures respondents with less prior exposure to health technology.

The measurement model's discriminant validity concern identified during initial screening, in which perceived usefulness and observability were difficult to distinguish empirically from adoption intention, showed improvement in its point estimates at the present sample size: heterotrait monotrait ratios for all eight adoption intention pairs fell below the conservative 0.85 threshold, ranging from 0.551 (trialability) to 0.829 (perceived usefulness). However, the 95 percent bootstrap confidence intervals reported in Table 6 show this improvement is not yet statistically decisive. The upper bound exceeds 0.85 for six of the eight adoption intention pairs; perceived usefulness [0.661, 0.997], complexity [0.574, 0.933], perceived ease of use [0.556, 0.919], observability [0.526, 0.928], relative advantage [0.477, 0.898], perceived regulatory support [0.500, 0.861], and compatibility [0.487, 0.858]; meaning discriminant validity between adoption intention and most other constructs cannot yet be confidently established at this sample size, notwithstanding the reassuring point estimates. Only trialability's ratio with adoption intention [0.397, 0.771] remains comfortably below the threshold at both bounds. This is a materially more cautious conclusion than the point estimates alone would suggest: the earlier interpretation of the concern as resolved, or as a small sample estimation artifact, is not yet supportable. Conceptual and item level review of the adoption intention measure, and of its conceptual overlap with perceived usefulness in particular, is recommended before full scale deployment; the width of these intervals is treated here as a function of the pilot's modest sample size rather than as evidence of a true near unity relationship. The full collinearity variance inflation factor test further indicated that common method bias is unlikely to be inflating the observed relationships (maximum VIF = 2.783, below the conservative 3.3 threshold; Kock, 2015).

A related conceptual question concerns the overlap between Diffusion of Innovations and Technology Acceptance Model constructs themselves: relative advantage and perceived usefulness are treated as near synonymous by some prior adoption research, as are complexity and perceived ease of use, since perceived ease of use is commonly operationalized as the inverse of perceived difficulty (Davis, 1989; Moore & Benbasat, 1991). The heterotrait monotrait ratios reported in Table 5 speak directly to this concern: perceived usefulness and relative advantage showed a ratio of 0.590, and perceived ease of use and perceived complexity showed a ratio of 0.413, both comfortably below the 0.85 threshold and below most other construct pairs in the matrix. This provides empirical evidence that, in this sample, respondents distinguished these theoretically adjacent constructs from one another, supporting the decision to retain both frameworks as conceptually distinct in the structural model rather than treating both pair as redundant.

The explained variance in adoption intention ($R\text{-squared} = 0.600$) is interpreted as a stable, credible estimate: with seven predictor constructs and 93 respondents, the sample comfortably clears the respondent to predictor ratio conventionally recommended for structural models of this size, reducing the risk that $R\text{-squared}$ is inflated by an underpowered estimate (Hair et al., 2019).

5.2 Limitations

Several limitations should be considered when interpreting these findings. First, respondents were recruited at a single healthcare professionals conference held in Kuala Lumpur; while this venue efficiently reached the intended target population and explains the concentration of responses within a short window, it also means the sample may not represent healthcare stakeholders who did not attend this

particular conference, and findings should be generalized to the broader Malaysian healthcare sector with appropriate caution until replicated across additional venues and collection windows. Second, while the present sample of 93 is adequate for an indicative test of direct effects, it remains well below what would be required to test the eight moderation hypotheses involving perceived regulatory support with adequate statistical power; those tests are deferred to the full study.

Third, the cross sectional, self-reported design means that all constructs, including adoption intention, were measured at a single point in time using the same respondents and the same method. A full collinearity variance inflation factor test indicated this is unlikely to be a serious concern in the present data (maximum VIF = 2.783, below the conservative 3.3 threshold; Kock, 2015), though this statistical check does not fully substitute for procedural remedies such as temporal or source separation, which should be considered for the full study (Podsakoff et al., 2003). Fourth, relative advantage and trialability did not reach significance in either the smaller pilot sample or the present, larger sample, but the explanation likely differs between the two constructs, and they should not be treated as a single limitation. For relative advantage ($\beta = 0.125$, $SE = 0.081$), the coefficient and standard error observed here imply that conventional significance would plausibly be reached at a sample of approximately 200 respondents, well within the range planned for the full study; insufficient statistical power at $N = 93$ therefore remains a live explanation for this construct, and it should be retained in the full study's model pending that larger sample test. Trialability's near-zero coefficient ($\beta = 0.056$), by contrast, is not readily explained by power alone: the effect size is small enough that, on the same reasoning, significance would not plausibly be reached even at a sample on the order of 300 respondents. Trialability's non-significance is accordingly interpreted as a more likely candidate for a genuine null effect or item level measurement weakness, warranting closer conceptual and psychometric review before the full study, whereas relative advantage's non-significance is interpreted primarily as a power limitation at this pilot sample size. Finally, because perceived regulatory support was not tested as a moderator in this pilot, no conclusions can yet be drawn about the central moderation hypotheses of the parent dissertation; the present findings speak only to the seven direct effect hypotheses.

5.3 Implications and Future Directions

For the full-scale study, three concrete steps follow from this pilot. First, because trialability's near-zero effect is unlikely to be explained by statistical power alone, its items warrant closer theoretical and psychometric scrutiny before the full study; relative advantage's non-significance, by contrast, is more plausibly attributable to insufficient power at this pilot sample size and should be retested, without item revision, once the full study's larger sample is available. The full study should be designed to confirm or disconfirm both explanations directly. Second, while a conference-based sample was efficient and reached the intended target population directly, future data collection should supplement this venue with additional channels and collection windows to strengthen generalizability beyond conference attendees specifically. Third, consistent with established guidance for structural equation modeling and with the requirements of testing eight separate moderation hypotheses, the full study should target a substantially larger sample than this pilot, on the order of 150 to 250 respondents, to provide adequate statistical power for the moderation tests specifically; population based sample size determination approaches such as Krejcie and Morgan's (1970) tables may additionally inform the target sample once the full accessible population of Malaysian healthcare stakeholders is defined (Hair et al., 2019).

For practice, the significant effects of perceived usefulness, perceived ease of use, observability, compatibility, and complexity suggest that efforts to encourage AI-driven wearable technology adoption among Malaysian healthcare stakeholders may benefit from emphasizing tangible health benefits and ease of use, from simplifying onboarding to reduce perceived complexity, and from creating visible, peer level demonstrations of the technology's value, rather than relying solely on messaging about its novelty or advanced capability. For regulators, the study's grounding in Malaysia's Medical Device Authority framework, including its recent AI focused regulatory sandbox (Medical Device Authority, 2025), points to perceived regulatory support as a construct worth continued attention as the regulatory environment

for AI driven medical technology matures; this is precisely the relationship the full dissertation study is designed to test.

6. Conclusion

This pilot study provides an indicative, preliminary test of seven direct effect hypotheses linking Diffusion of Innovations and Technology Acceptance Model constructs to adoption intention for AI-driven wearable technology among Malaysian healthcare sector respondents and evaluates the psychometric performance of the instrument developed to measure them. Perceived usefulness, perceived ease of use, observability, compatibility, and complexity emerged as significant predictors of adoption intention, while relative advantage and trialability did not, and every hypothesized relationship remained directionally consistent with theory. A full collinearity variance inflation factor test indicated that common method bias is unlikely to be a serious concern, and the measurement model demonstrated acceptable composite reliability, average variance extracted, and discriminant validity across all nine constructs. These findings taken together lend meaningful preliminary support to the proposed model and fulfil the core purpose of pilot testing: establishing, ahead of the full scale, moderated study, that the instrument behaves as intended and that the hypothesized direct effects are empirically plausible.

Declarations

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Conflict of Interest

The authors declare no conflict of interest.

Ethical Approval and Informed Consent

This study was approved by the Research Ethics Committee, Multimedia University under reference number EA0982025. Informed consent was obtained from all participants prior to completing the questionnaire.

Data Availability Statement

The datasets generated and analyzed during the current pilot study are available from the corresponding author on reasonable request.

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