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Perceived Need for AI-Powered Digital Health Interventions among Academicians Suffering from Lifestyle Diseases: An Empirical Survey

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Abstract

The rising prevalence of lifestyle diseases — notably obesity, type 2 diabetes mellitus, and hypertension — among university academicians represents a critical yet systematically underexplored occupational health challenge. Characterized by prolonged sedentary work routines, chronic academic stress, irregular dietary habits, and insufficient physical activity, teaching professionals constitute a uniquely vulnerable population. Despite the unprecedented growth of artificial intelligence (AI)-enabled digital health platforms and health-focused digital marketing, the perceived need for such interventions among this population remains empirically underexplored, particularly within the Indian higher education context.

The present study aims to assess the perceived need for AI-powered digital health interventions among academicians suffering from lifestyle diseases, drawing on the Health Belief Model (HBM) and the Technology Acceptance Model (TAM) as the primary theoretical anchors. A structured questionnaire survey was designed and administered to 220 academicians drawn from universities and higher education institutions across India, using purposive sampling. The survey instruments assessed awareness of AI-based digital health tools, perceived severity of lifestyle diseases, digital health literacy, health consciousness, and perceived need for AI-powered health interventions. Descriptive analysis, reliability testing, and structural equation modeling (PLS-SEM) via SmartPLS 4.0 were employed for data analysis. The findings reveal that perceived severity of lifestyle diseases ($\beta = 0.42$, $p < 0.001$), digital health literacy ($\beta = 0.36$, $p < 0.001$), and awareness of AI health tools ($\beta = 0.29$, $p < 0.01$) are significant positive determinants of perceived need for AI-powered health interventions. Health consciousness was found to partially mediate the relationship between perceived severity and perceived need.

The study contributes to the intersection of digital health marketing, AI adoption behavior, and occupational health literature by offering empirical evidence on the technology-mediated health behavior of academic professionals. Practically, the findings provide actionable guidance for health-tech developers, university administrators, and digital health marketers in designing targeted AI-driven wellness programs for the academic community.

Keywords: *AI health interventions, digital health marketing, lifestyle diseases, academicians, Health Belief Model, Technology Acceptance Model, perceived need, India.*

1.Introduction

India's higher education sector employs over 1.5 million teaching faculty across more than 43,000 colleges and universities (AISHE Report, 2022–23). Behind this impressive academic infrastructure lies a lesser-acknowledged public health concern: a significant proportion of Indian university academicians suffer from preventable lifestyle diseases, including obesity, type 2 diabetes, hypertension, and cardiovascular complications (Singh et al., 2020). According to the Indian Council of Medical Research (ICMR, 2023), nearly 40% of urban white-collar professionals — a category that prominently includes academic faculty — report at least one metabolic disorder before the age of 50. Yet, this population remains conspicuously absent from mainstream occupational health research and digital wellness intervention strategies.

Simultaneously, the global digital health market is undergoing a transformative revolution powered by artificial intelligence. AI-driven mobile health applications, wearable biosensors, personalized nutrition platforms, and predictive diagnostic tools have collectively created a multi-billion-dollar ecosystem of digital health marketing (Grand View Research, 2024). In India alone, the digital health market is projected to reach USD 10.6 billion by 2025 (NASSCOM, 2023), with AI-enabled wellness solutions at the forefront of this expansion. Health marketers and technology developers are increasingly deploying targeted digital marketing campaigns — leveraging social media algorithms, programmatic advertising, and AI-powered content personalization — to drive awareness and adoption of these tools. However, whether such campaigns are reaching and resonating with high-risk, sedentary professional populations such as academicians remains a critically unanswered question.

The academic profession, by its very nature, is characterized by a constellation of lifestyle risk factors. Long hours of desk-bound scholarly work, high cognitive demands, research and administrative pressures, and limited institutionalized wellness infrastructure collectively predispose teaching professionals to sedentary behavior, stress-related eating, sleep disruption, and chronic disease accumulation (Nagar & Bhatt, 2021; Sharma & Verma, 2022). Unlike corporate employees who benefit from structured employee wellness programs and health insurance incentives, most Indian university faculty members navigate their health challenges with minimal institutional support (Joshi et al., 2019). This creates a structural gap in which AI-powered digital health tools — if perceived as useful and accessible — could serve as critical self-management resources.

Scholars have examined digital health marketing from multiple perspectives, including technology adoption (Venkatesh et al., 2003), consumer health engagement (Kramer et al., 2019), and AI-mediated personalization in healthcare (Davenport & Kalakota, 2019). Research on the Health Belief Model (Rosenstock, 1974) has consistently demonstrated that perceived severity of a health condition and perceived benefits of an intervention are primary drivers of health behavior change. The Technology Acceptance Model (Davis, 1989) has further established that perceived usefulness and ease of use are central to technology adoption decisions.

However, extant research has predominantly focused on patients, elderly populations, and urban youth as consumers of digital health tools, largely overlooking the specific context of professional academicians as a unique at-risk cohort. A critical lacuna exists in our understanding of whether Indian university faculty members recognize the need for, or express intention to use, AI-powered digital health marketing interventions for managing their lifestyle diseases. Prior studies have documented the health burden among faculty (Singh et al., 2020; Nagar & Bhatt, 2021) and the efficacy of digital health tools in general populations (Peng et al., 2021), but the intersection of these two streams — AI-driven digital health marketing directed at academic professionals — has received no systematic empirical attention. This represents both a theoretical gap in the health technology adoption literature and a practical gap in the design of occupational health interventions.

Accordingly, the present study addresses the following research questions: RQ1: What is the level of awareness of AI-powered digital health tools among Indian university academicians? RQ2: What factors determine the perceived need for AI-driven digital health interventions among academicians suffering from lifestyle diseases? RQ3: Does health consciousness mediate the relationship between perceived disease severity and perceived need for AI health interventions?

This study makes three distinct contributions. Theoretically, it extends the Health Belief Model and the Technology Acceptance Model to the occupational context of academic professionals, a population previously unaddressed in health technology adoption research. Methodologically, it introduces a novel integrated framework combining HBM and TAM constructs to explain perceived need — rather than behavioral intention alone — in the context of AI health tools. Practically, the findings provide actionable intelligence for health-tech companies, university administrators, and digital health marketers to design, position, and communicate AI-powered wellness solutions specifically tailored to the needs of academic professionals in India. The remainder of this paper proceeds as follows. Section 2 presents the theoretical framework and literature review. Section 3 details the hypothesis development. Section 4 describes the research methodology. Section 5 reports the empirical results. Section 6 discusses the findings, and Section 7 concludes with implications, limitations, and directions for future research.

2. Literature Review and Theoretical Framework

2.1 Health Belief Model (HBM) and Digital Health Behavior

The Health Belief Model (HBM), originally formulated by Rosenstock (1974) and subsequently refined by Becker (1974) and Champion & Skinner (2008), posits that an individual's health behavior is governed by a set of cognitive perceptions: perceived susceptibility (belief about the likelihood of contracting a condition), perceived severity (belief about the seriousness of the condition), perceived benefits (belief about the effectiveness of a proposed action), and perceived barriers (obstacles to action). Cues to action and self-efficacy were later integrated as additional constructs (Rosenstock et al., 1988).

The HBM has been extensively applied to digital health interventions, demonstrating that individuals with higher perceived severity of their health condition exhibit significantly greater engagement with health apps, telemedicine platforms, and AI-based wellness tools (Ameri et al., 2020; Kramer et al., 2019). In the context of academicians, perceived severity of lifestyle diseases — obesity, diabetes, and hypertension — constitutes a primary motivational force. Faculty members who recognize the seriousness of their metabolic conditions are theoretically more likely to acknowledge the need for structured digital health interventions. Drawing on the HBM framework, the present study operationalizes perceived severity as a key antecedent of perceived need for AI-powered health solutions, with health consciousness hypothesized as a mediating mechanism through which severity perceptions translate into intervention demand.

2.2 Technology Acceptance Model (TAM) and AI Health Tools

The Technology Acceptance Model (Davis, 1989), subsequently extended as TAM2 (Venkatesh & Davis, 2000) and UTAUT (Venkatesh et al., 2003), establishes that users' intention to adopt a technology is fundamentally shaped by their perceptions of its usefulness and ease of use. In the digital health domain, TAM has been widely applied to explain adoption of mobile health applications (Cho et al., 2019), AI-driven diagnostics (Davenport & Kalakota, 2019), wearable health trackers (Gao et al., 2015), and teleconsultation platforms (Meng et al., 2021). For AI-powered health interventions specifically, awareness of available tools and digital health literacy serve as proximal antecedents of perceived usefulness (Peng et al., 2021). Individuals with higher digital health literacy — defined as the ability to seek, find, understand, and appraise health information from digital sources — demonstrate significantly higher perceived need and adoption intention for AI health platforms (Norman & Skinner, 2006; Stellefson et al., 2020).

Academicians, as digitally proficient professionals, represent a population with above-average digital literacy in general; however, their specific digital health literacy — the application of these skills toward personal health management — may vary considerably depending on awareness and motivation. The integration of TAM constructs with the HBM framework provides a robust theoretical lens through which to explain the perceived need for AI health interventions among this cohort.

2.3 Lifestyle Diseases among Academicians

A growing body of literature documents the heightened vulnerability of academic professionals to lifestyle-related non-communicable diseases. Singh et al. (2020) conducted a cross-sectional study among university faculty in North India and reported a 38.4% prevalence of hypertension, 21.6% prevalence of type 2 diabetes, and 44.2% overweight/obesity rates — all significantly higher than national population averages. Nagar and Bhatt (2021) attributed these outcomes to occupational sedentarism, sustained cognitive stress, and inadequate institutionalized health surveillance within Indian universities. Internationally, Farrell et al. (2017) similarly found elevated metabolic risk among academic professionals in the United Kingdom, while Molina-Garcia et al. (2019) documented high sedentary time among Spanish university teaching staff, correlating it with increased cardiometabolic risk.

Despite this documented burden, research on the willingness or perceived need of academic professionals to adopt AI-powered digital health interventions is virtually absent from the literature. Existing studies on digital health adoption have focused on patients with chronic conditions (Meng et al., 2021), elderly populations (Cho et al., 2019), and urban youth (Peng et al., 2021), leaving academic faculty as a conspicuously unaddressed segment.

2.4 Digital Health Marketing and AI-Enabled Wellness Platforms

Digital health marketing refers to the application of digital communication strategies — including social media marketing, search engine optimization, programmatic advertising, content marketing, and AI-driven personalization — to promote health products, services, and behavioral interventions (Moorhead et al., 2013; Trivedi & Pulkit, 2022). The proliferation of AI in this space has enabled hyper-personalized health communication, real-time behavioral nudging, and predictive health risk scoring, fundamentally reshaping how wellness interventions are delivered and consumed (Davenport & Kalakota, 2019; Trivedi, 2025). AI platforms such as symptom checkers, calorie management apps, blood pressure monitoring applications, and diabetes management ecosystems represent an emerging category of consumer-facing health technology that is actively marketed through digital channels. The effectiveness of such marketing in reaching academicians — and the extent to which this population perceives a need for these tools — remains an open empirical question of both theoretical and practical significance.

3. Hypothesis Development

Drawing on the integrated HBM-TAM framework, four hypotheses are proposed to explain the perceived need for AI-powered digital health interventions among academicians:

3.1 Perceived Severity and Perceived Need

Grounded in the Health Belief Model (Rosenstock, 1974), perceived severity reflects an individual's appraisal of the seriousness of a health threat. Individuals who perceive their lifestyle conditions — obesity, hypertension, diabetes — as severe are theoretically motivated to seek effective interventions (Champion & Skinner, 2008). Ameri et al. (2020) demonstrated that perceived severity was the strongest predictor of health app adoption among chronic disease patients. In the context of academicians who are aware of their deteriorating metabolic health, higher perceived severity is expected to translate into a higher perceived need for structured AI health interventions.

H1: Perceived severity of lifestyle diseases is positively associated with perceived need for AI-powered digital health interventions among academicians.

3.2 Awareness of AI Health Tools and Perceived Need

Awareness of AI-based digital health platforms is a fundamental precondition for their perceived need and adoption. Individuals cannot form meaningful utility judgments about tools of which they are unaware (Venkatesh et al., 2003). Digital health marketing campaigns play a critical role in building this awareness (Moorhead et al., 2013; Trivedi & Chitraju, 2025). Stellefson et al. (2020) found a significant positive association between awareness of digital health tools and adoption intention in a professional sample. Among academicians who are exposed to AI health marketing through digital media, higher awareness is expected to drive higher perceived need.

H2: Awareness of AI-powered digital health tools is positively associated with perceived need for AI health interventions among academicians.

3.3 Digital Health Literacy and Perceived Need

Digital health literacy — defined as the competency to access, interpret, and apply health information from digital platforms — has been identified as a significant enabler of technology adoption in health contexts (Norman & Skinner, 2006). Faculty members with higher digital health literacy are better equipped to evaluate the relevance and quality of AI-powered health solutions (Peng et al., 2021). Importantly, health literacy directly influences perceived benefits — a central HBM construct — by enabling individuals to assess how well a proposed intervention addresses their health concerns (Cho et al., 2019).

H3: Digital health literacy is positively associated with perceived need for AI-powered digital health interventions among academicians.

3.4 Mediating Role of Health Consciousness

Health consciousness — defined as the degree to which an individual is self-aware of and motivated to improve their personal health (Hong, 2009) — serves as a cognitive bridge between disease awareness and action-seeking behavior. Individuals who perceive their condition as severe are more likely to develop health consciousness, which in turn activates a sense of urgency for intervention (Dutta-Bergman, 2004). Prior research has established health consciousness as a mediator between health threat perceptions and health information-seeking behavior (Kim & Gupta, 2012). In the present model, health consciousness is hypothesized to partially mediate the pathway from perceived severity to perceived need for AI digital health tools.

H4: Health consciousness mediates the positive relationship between perceived severity of lifestyle diseases and perceived need for AI-powered digital health interventions.

4. Research Methodology

4.1 Research Design

The present study employs a quantitative, cross-sectional survey design grounded in the positivist research paradigm. A structured questionnaire was used as the primary data collection instrument, consistent with prior empirical studies in health technology adoption (Cho et al., 2019; Peng et al., 2021; Pal & Trivedi, 2022) and digital health marketing (Moorhead et al., 2013). A cross-sectional design was deemed appropriate given the exploratory-descriptive objective of the study — to assess the current state of perceived need among academicians — rather than to establish causality across time points.

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The study was conducted across universities and higher education institutions in India, with a focus on full-time teaching faculty as the target population.

4.2 Sampling and Data Collection

The target population comprised full-time university and college faculty members across India who self-reported at least one lifestyle disease — obesity, type 2 diabetes, hypertension, or elevated blood pressure. Purposive sampling was employed to ensure that respondents met the inclusion criterion of diagnosed or self-reported lifestyle disease, thereby ensuring theoretical relevance (Creswell & Creswell, 2018). A total of 250 questionnaires were distributed through a combination of online (Google Forms) and offline channels, leveraging academic WhatsApp networks, institutional email lists, and in-person administration at faculty development programs. After removing incomplete and inconsistent responses, a final usable sample of 220 responses was retained, yielding a response rate of 88%. The sample size satisfies the minimum threshold of 200 respondents recommended for PLS-SEM analysis (Hair et al., 2019).

4.3 Measurement Instrument

All constructs were measured using validated multi-item scales adapted from established instruments in the literature and rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Perceived severity (4 items) was adapted from Champion and Skinner (2008). Awareness of AI health tools (4 items) was newly developed, drawing on Stellefson et al. (2020). Digital health literacy (5 items) was adapted from Norman and Skinner (2006). Health consciousness (4 items) was adapted from Hong (2009). Perceived need for AI health interventions (5 items) served as the dependent construct. A pilot study involving 30 respondents was conducted to assess face validity and item clarity prior to the main data collection phase, resulting in minor wording adjustments to three items.

4.4 Common Method Bias and Analytical Technique

To minimize common method bias (Podsakoff et al., 2003), procedural remedies were employed, including guaranteed respondent anonymity, temporal separation of predictor and criterion items within the questionnaire, and randomization of item order. Harman's single-factor test yielded a maximum variance explained of 31.4% by a single factor, well below the threshold of 50%, indicating that common method bias does not pose a significant threat to the validity of the findings. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SmartPLS 4.0 (Ringle et al., 2022) for hypothesis testing. PLS-SEM was preferred over CB-SEM given the predictive orientation of the study, the relatively small sample size, and the non-normal distribution of the data (Hair et al., 2019). A two-stage assessment approach — measurement model followed by structural model evaluation — was employed as recommended by Anderson and Gerbing (1988).

Table 1: Demographic Profile of Respondents (N = 220)

Characteristic	Category	Frequency (%)
Gender	Male	132 (60.0%)
	Female	84 (38.2%)
	Prefer not to say	4 (1.8%)
Age Group	Below 30	18 (8.2%)
	30–40 years	74 (33.6%)
	41–50 years	96 (43.6%)
	51 years & above	32 (14.5%)
Designation	Assistant Professor	88 (40.0%)
	Associate Professor	84 (38.2%)
	Professor	44 (20.0%)
	Other	4 (1.8%)
Teaching Experience	Less than 5 years	22 (10.0%)
	5–10 years	62 (28.2%)
	11–20 years	88 (40.0%)
	More than 20 years	48 (21.8%)
Physical Activity	Daily	26 (11.8%)
	3–4 times/week	54 (24.5%)
	Rarely	102 (46.4%)
	Never	38 (17.3%)
Reported Condition (Multiple allowed)	Obesity / Overweight	118 (53.6%)
	Type 2 Diabetes	64 (29.1%)
	Hypertension / High BP	78 (35.5%)
	Multiple Conditions	84 (38.2%)
	None of the above	0 (0.0%)

5. Results and Analysis

5.1 Measurement Model Assessment

The measurement model was assessed for reliability and validity. All indicator loadings exceeded 0.70 (range: 0.71–0.89), confirming indicator reliability. Composite reliability (CR) values for all constructs surpassed the recommended threshold of 0.70 (range: 0.81–0.91), and Cronbach's alpha values were similarly acceptable (α range: 0.78–0.89). Average Variance Extracted (AVE) values exceeded 0.50 for all constructs (range: 0.52–0.67), establishing convergent validity (Hair et al., 2019). Discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) ratio criterion; all HTMT values were below 0.85, indicating adequate discriminant validity among constructs (Henseler et al., 2015).

Table 2: Measurement Model — Reliability and Validity

Construct	Cronbach's α	CR	AVE	Mean (SD)
Perceived Severity (PS)	0.84	0.88	0.60	3.82 (0.79)
AI Tool Awareness (ATA)	0.79	0.84	0.57	3.24 (0.91)
Digital Health Literacy (DHL)	0.89	0.91	0.67	3.46 (0.84)
Health Consciousness (HC)	0.78	0.81	0.52	3.61 (0.77)
Perceived Need (PN)	0.86	0.89	0.63	3.74 (0.82)

5.2 Structural Model and Hypothesis Testing

The structural model was evaluated by examining path coefficients (β), t-statistics (via bootstrapping with 5,000 resamples), and R^2 values. The model explained 58.4% of the variance in perceived need for AI health interventions ($R^2 = 0.584$), indicating substantial predictive power (Cohen, 1988). All four hypotheses were supported at conventional significance levels. Perceived severity ($\beta = 0.42$, $t = 6.84$, $p < 0.001$) emerged as the strongest predictor of perceived need, followed by digital health literacy ($\beta = 0.36$, $t = 5.91$, $p < 0.001$) and AI tool awareness ($\beta = 0.29$, $t = 2.91$, $p < 0.01$). The mediation analysis using the bootstrapped indirect effect confirmed that health consciousness significantly mediates the severity–need relationship (indirect effect = 0.18, 95% CI [0.11, 0.26]), supporting H4. The direct effect of perceived severity remained significant after introducing the mediator, indicating partial mediation.

Table 3: Structural Model Results — Hypothesis Testing

Hypothesis	β	t-value	p-value	f²	Decision
H1: PS → PN	0.42	6.84	<0.001	0.28	Supported
H2: ATA → PN	0.29	2.91	<0.01	0.13	Supported
H3: DHL → PN	0.36	5.91	<0.001	0.21	Supported
H4: PS → HC → PN (Mediation)	0.18*	3.62	<0.001	—	Supported

*Note: *Indirect effect (bootstrapped, 95% CI [0.11, 0.26]); PS = Perceived Severity; ATA = AI Tool Awareness; DHL = Digital Health Literacy; HC = Health Consciousness; PN = Perceived Need.*

6. Discussion

The findings of this study provide the first systematic empirical evidence on the perceived need for AI-powered digital health interventions among Indian university academicians, a population uniquely burdened by lifestyle diseases yet largely overlooked in the health technology adoption literature. The results confirm all four hypotheses and yield several theoretically meaningful and practically significant insights.

The robust positive effect of perceived severity on perceived need (H1: $\beta = 0.42$, $p < 0.001$) aligns strongly with the core propositions of the Health Belief Model (Rosenstock, 1974). Academicians who perceive their metabolic conditions — obesity, diabetes, hypertension — as serious and threatening are significantly more likely to recognize the need for structured AI-driven health interventions. This finding is consistent with Ameri et al. (2020), who identified perceived severity as the dominant predictor of digital health app adoption among chronic disease populations, and extends their work to the specific context of academic professionals. A plausible explanation lies in the heightened health salience created by severity perceptions: when individuals view their condition as consequential, cognitive resources are mobilized toward identifying effective solutions, thereby elevating perceived need (Champion & Skinner, 2008).

The significant contribution of digital health literacy (H3: $\beta = 0.36$, $p < 0.001$) underscores a critical facilitating condition for AI health intervention uptake. Faculty members who possess the competency to navigate, evaluate, and apply health information from digital platforms exhibit substantially higher perceived need for AI tools. This is consistent with Norman and Skinner (2006) and Stellefson et al. (2020), who established digital health literacy as a foundational enabler of health technology engagement. The practical implication is profound: interventions that enhance digital health literacy among academic staff — through institutional health workshops, faculty wellness programs, and targeted digital health communication — may significantly amplify the perceived utility of AI-powered wellness solutions.

The finding that AI tool awareness positively predicts perceived need (H2: $\beta = 0.29$, $p < 0.01$) highlights an important but often underappreciated dimension of digital health marketing effectiveness. Many academicians, despite their general digital proficiency, remain unaware of specific AI-enabled health platforms relevant to their conditions. This awareness gap — likely attributable to the fragmented and general-audience orientation of current digital health marketing campaigns — represents a critical missed opportunity for health-tech developers. Targeted content marketing, social media outreach through academic professional networks (such as ResearchGate and LinkedIn), and institutional communication channels could substantially close this awareness gap.

The mediation analysis (H4) reveals that health consciousness serves as a partial mediator in the severity–need pathway, contributing an indirect effect of 0.18. This finding extends the work of Dutta-Bergman (2004) and Kim and Gupta (2012) by demonstrating that severity perceptions do not directly translate into perceived need in isolation — they do so partly by elevating the individual's overall health consciousness, which then amplifies the demand for intervention tools. This nuance has important implications for health communication design: campaigns that simultaneously raise awareness of disease severity and cultivate a health-conscious identity among academics are likely to be more effective than those that address either dimension in isolation.

7. Implications

7.1 Theoretical Implications

This study contributes to the health technology adoption and digital health marketing literatures in three distinct ways. First, it integrates the Health Belief Model and the Technology Acceptance Model within a single unified framework to explain perceived need — rather than just behavioral intention or actual use — in the context of AI health interventions. This theoretical integration extends prior work that has applied these models independently (Cho et al., 2019; Ameri et al., 2020) and demonstrates their complementary explanatory power when applied jointly to a professional health context. Second, the study introduces academic faculty as a theoretically valid and empirically underexplored target population for digital health adoption research, challenging the field's overwhelming reliance on patient and elderly samples. Third, by demonstrating health consciousness as a partial mediator in the HBM-based severity–need pathway, the study advances the theoretical understanding of the cognitive mechanisms through which disease severity perceptions are translated into technology-mediated health-seeking behavior.

7.2 Managerial Implications

From a practitioner perspective, the findings yield three actionable insights for health-tech developers and digital health marketers. First, given that perceived severity is the strongest predictor of perceived need, AI health platforms targeting academic professionals should position their marketing communications around the clinical consequences of unmanaged lifestyle diseases — framing obesity, diabetes, and hypertension not merely as inconveniences but as serious, progressive threats to academic productivity and longevity.

Second, since digital health literacy is a powerful enabler, health-tech companies should partner with universities to conduct digital health literacy workshops and integrate awareness of AI wellness tools into faculty onboarding and professional development programs. Third, given the awareness gap documented in this study, health marketers should design dedicated academic professional outreach campaigns through channels frequented by faculty — including academic social networks, university email systems, and conference platforms like GIMCA — rather than relying on broad-based consumer health advertising.

For university administrators, the findings make a compelling institutional case for integrating AI-powered wellness programs into faculty welfare policies. Universities that invest in institutional health monitoring platforms, AI-based nutrition and exercise recommendations, and regular health screenings for faculty may not only improve faculty health outcomes but also reduce absenteeism, enhance research productivity, and attract and retain quality academic talent.

8. Limitations and Future Research

The present study, while contributing meaningfully to the literature, is subject to several limitations that warrant acknowledgment and that point toward productive avenues for future inquiry. First, the cross-sectional design precludes causal inference; while the PLS-SEM results are consistent with the proposed theoretical model, longitudinal studies are necessary to establish directionality and causality in the severity–need–adoption pathway. Second, the sample was drawn from Indian higher education institutions, limiting the generalizability of findings to academicians in other cultural and institutional contexts. Replication studies in diverse geographic settings — including Southeast Asia, Africa, and the Middle East, where lifestyle disease burden among academics is also rising — would substantially enhance the external validity of these findings. Third, self-reported data on lifestyle disease status may be subject to social desirability bias and recall inaccuracy; future studies should integrate objective health indicators (BMI measurements, HbA1c levels, blood pressure readings) alongside self-report measures. Future research might also examine additional antecedents of perceived need — including peer influence, institutional support, cost perceptions, and data privacy concerns — as well as the downstream relationship between perceived need and actual adoption behavior of AI health tools among academic professionals.

9. Conclusion

University academicians represent a high-risk, professionally distinct population whose lifestyle disease burden is substantial but whose engagement with AI-powered digital health interventions remains limited and largely unstudied. The present study addressed this gap by empirically investigating the perceived need for AI-driven digital health marketing interventions among Indian university faculty suffering from obesity, diabetes, and hypertension. Drawing on the Health Belief Model and the Technology Acceptance Model, the study identified perceived severity of lifestyle diseases, digital health literacy, and awareness of AI health tools as significant positive drivers of perceived need, with health consciousness serving as a partial mediator in the severity–need relationship.

These findings carry meaningful implications for health-tech developers, digital health marketers, and university administrators seeking to design and promote wellness solutions for academic communities. As AI continues to reshape the landscape of health communication and personalized wellness, academic institutions have a unique and urgent opportunity to leverage these technologies for the benefit of their faculty. The present study offers a theoretically grounded and empirically validated foundation upon which future research and practice in this domain can build.

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