AACOM
American Association of Colleges of Osteopathic Medicine

Executive Summary

AI adoption is broad but shallow, and training needs are universal

Six in ten College of Osteopathic Medicine COM faculty use AI at least weekly, yet 56% self-identify as beginners and only 7% as advanced. Large language models (LLMs) dominate adoption (62% of users); all other tool categories—virtual patients, simulation analytics, NLP-based assessment—remain below 7%. Training needs are elevated across all eight surveyed domains, with the greatest demand in AI-enabled assessment and feedback (M = 3.57/5), policy and governance (M = 3.50) and curriculum design (M = 3.47). Faculty who have never used AI report the lowest training needs across every domain—an exposure paradox suggesting that engagement itself surfaces awareness of skill gaps. No significant differences in training needs exist by career stage, and clinical and non-clinical faculty converge on the same top priorities (foundational literacy, hands-on tools), supporting a universal faculty development core with role-sensitive depth.

Clinical faculty report higher needs and different tools, not different priorities

Clinical faculty report significantly higher training needs than non-clinical colleagues in basic AI concepts ($p = .003$), AI-enabled study tools ($p = .013$) technical skills ($p = .037$) and the composite need score is higher ($M = 3.43$ vs. 3.25). The groups diverge most sharply in which technologies they use: 32% of clinical faculty use EHR tools with AI features versus 9% of non-clinical faculty ($p < .001$), and clinical faculty rank EHR-driven simulations significantly higher as a development priority ($p = .016$). Within clinical faculty, the exposure paradox is pronounced: AI use frequency is significantly associated with training needs across all eight domains, while among non-clinical faculty this relationship is significant in only two of eight domains. No differences emerge between clinical physicians and non-physician clinicians, though the small non-physician sample ($n = 22$) limits that conclusion.

Faculty are ready; institutions are not—and half don't know where they stand

Two-thirds of faculty agree AI will improve their effectiveness, and nearly half intend to incorporate AI within 12 months. But only 19% agree their institution is using AI effectively, only 15% say their institution is ahead of the curve and 49.5% of faculty are unsure whether their COM has any AI policies at all. Clinical faculty are disproportionately unsure (Cramér's $V = 0.223$). Where faculty confirm no policies exist, well-being indicators are worst: emotional exhaustion is highest and workplace belonging lowest. Policy communication—not institutional identity (ICC < 1%)—is the modifiable variable.

AI attitudes connect to well-being through workplace climate, not through use

A cluster analysis of workplace belonging, emotional exhaustion, professional passion and AI attitudes identifies four faculty profiles. Two thriving groups share strong well-being but diverge sharply in AI attitudes—demonstrating that high well-being is compatible with either enthusiasm or caution toward AI. Distress and disengagement coincide with below-average AI attitudes but, critically, the disengaged group also reports the lowest training needs despite using the fewest tools. Across the full sample, AI attitudes—not use frequency—are associated with professional passion, and belonging predicts more favorable AI attitudes. Burnout is decoupled from AI engagement entirely.

Implications for AACOM and member institutions

These findings support a shared AI faculty development core anchored in foundational literacy, hands-on tool training, assessment integration and policy frameworks—with EHR-focused depth for clinicians and targeted re-engagement for disengaged faculty who report low needs yet use few tools. Because policy

communication is linked to both AI attitudes and well-being, institutional AI governance should be treated as a faculty support intervention, not solely as a compliance exercise.

Suggested citation:
Speicher, MR. Faculty Development Needs in AI and Faculty Well-being survey. American Association of Colleges of Osteopathic Medicine (AACOM), Bethesda, MD, April, 2026.

Research Objective

The research objectives for this survey were to describe the AI use and development needs by College of Osteopathic Medicine (COM) faculty. Survey questions for this survey were combined with AACOM's biennial faculty well-being survey. This survey was fielded in the fall and winter of 2025; a similar survey on general faculty development needs and well-being was fielded in the fall of 2023.

This survey was taken by willing faculty in the fall of 2025. AACOM distributed this survey through its faculty listservs; faculty at all COMs were included. The survey included four sections: demographics and teaching experience; attitudes towards AI and faculty development needs; questions about faculty well-being; and attitudes toward their workplaces. While the technology of AI itself, and therefore faculty development needs and attitudes surrounding AI, are changing rapidly, this report provides both a snapshot of those needs and attitudes among osteopathic faculty in the fall of 2025, as well as a baseline for future planning and discovery.

Discovery 1: AI Adoption Patterns and Convergent Training Needs Across Roles and Faculty Profiles

Across 49 COMs, faculty report frequent but shallow engagement with AI. Weekly use is common (compared to more or less frequent use) and most faculty members self-identify as beginners; large language models (LLMs) are the dominant tool class. Despite role- and career-stage heterogeneity in specific technologies and comfort, AI training needs converge strongly in content which supports a universal AI development core with role-sensitive depth and targeted outreach.

Discovery 2: AI Attitudes, Independent of AI Use, Link Workplace Climate to Professional Well-Being

Across osteopathic medical school faculty, more positive attitudes toward AI consistently align with higher professional passion and better facets of well-being, independent of how often faculty actually use AI. Workplace belonging relates to more favorable AI attitudes and greater stated AI training needs, and the link between belonging and passion is partially mediated by AI attitudes; AI engagement itself shows no association with emotional exhaustion, and any link between training needs and exhaustion is marginal and practically negligible.

Discovery 3: Policy Awareness, Not Institutional Identity, Predicts AI Attitudes and Well-Being

Institutional identity explained virtually none of the variance in faculty AI use; instead, individual-level awareness of institutional AI policy stratified both AI attitudes and well-being. Clear AI policies aligned with more positive AI attitudes, a confirmed policy vacuum aligned with the highest emotional exhaustion, lowest belonging and elevated AI training needs among COM faculty. Those unsure about policy status reported worse exhaustion than those with clarity, a pattern not moderated by role, gender or AI use.

AACOM
American Association of Colleges of Osteopathic Medicine

Methods and Data

Survey Design

The AACOM Faculty Survey on Faculty AI Development Needs and Workplace Well-Being was developed as a cross-sectional, self-administered online questionnaire distributed in the fall of 2025 through AACOM's faculty listservs to faculty and preceptors at all COMs in the United States. The survey was hosted on the AACOM Qualtrics server, and participation was voluntary and anonymous. The instrument combined items from validated measures of faculty well-being with researcher-developed items assessing AI engagement, perceptions, training needs and institutional policy awareness.

The survey comprised of the following sections relevant to this report: (a) Profile (six items: gender identity, race/ethnicity, professional role, employment status, years of experience in osteopathic medical education and institutional affiliation); (b) Prior exposure to digital health (two items: AI use frequency and self-rated AI familiarity); (c) Perceptions of technology (10Likert-type items on a five-point scale from Strongly Disagree to Strongly Agree); (d) Current practices and needs (four items including AI technologies currently used and self-rated training needs across eight domains); (e) Institutional environment and policy (three items on institutional AI policy status); (f) Priority-setting (rank-ordering of six faculty development priority areas); and (g) Technology adoption (two items on general technology adoption propensity and personal generative AI use). Additional sections on well-being, workplace environment and competency-based medical education were included in the full survey but are not analyzed in this report, except as AI attitudes and faculty development needs were associated with workplace features and faculty well-being.

Variables and Measures

AI use frequency was measured on a five-point ordinal scale (Daily, Weekly, Monthly, I've used it a few times, Never). AI familiarity was self-rated on a four-level scale (No familiarity, Beginner, Intermediate, Advanced). Training needs were assessed across eight domains (basic AI concepts, ethics and professionalism, AI-enabled study tools, AI in assessment and feedback, AI for curriculum design, EHR data for simulations, policy and governance, and technical skills), each rated on a five-point scale from No need for training (1) to Urgent need for training (5).

Professional role was a multi-select variable. For analytic purposes, respondents were classified into two groups: clinical faculty (any respondent selecting COM faculty—clinical physician or COM faculty—clinical non-physician, including those who also selected other roles) and non-clinical faculty (all others, including basic science faculty, simulation educators, clerkship directors, curriculum developers and administrators). Within clinical faculty, a subcategory distinguishing physician from non-physician clinicians was applied where sample sizes permitted.

Analytic Approach

All available responses were included in each analysis (i.e., respondents were not restricted to only those who completed the full survey), with the effective number of respondents reported for each question.

Descriptive statistics include frequencies and percentages for categorical variables and means with standard deviations for ordinal scales treated numerically (training needs). Cross-tabulations were tested with Pearson's chi-square test of independence; where expected cell counts were small, results should be interpreted with caution. Effect sizes for two-group comparisons are reported as Cramér's V for nominal associations. Differences in ordinal training-need ratings across groups were evaluated with Kruskal-Wallis H tests (three or more groups) and Mann-Whitney U tests (two groups). All tests were two-tailed at $\alpha = .05$. Analyses were conducted in Python 3.12 using pandas, SciPy and NumPy.

Descriptive Analysis of Survey Respondents and AI Needs

Response Overview

The survey yielded 715 responses from faculty and preceptors across 49 COMs (median responses per institution = 8; range 1–48). Of these, 466 (65.2%) completed the full survey and completion rates for the AI-related items were substantially higher than for the well-being items appearing later in the survey, supporting this inclusive approach. The following descriptive analysis uses all available responses for each item, with n reported per question.

Respondent Demographics

Table 1., below, summarizes the demographic characteristics of the sample.

Characteristic	Category	n	%
Gender	Female/woman	326	50.3
	Male/man	292	45.1
	Other/Prefer not to respond	30	4.6
Race/Ethnicity	White	454	70.3
	Asian	71	11.0
	Black or African-American	25	3.9
	Hispanic or Latino	22	3.4
	Multiracial	25	3.9
	Prefer not to respond	46	7.1
	American Indian or Alaskan Native	1	0.2
Employment Status	Full-time	505	78.3
	Part-time	140	21.7

Characteristic	Category	n	%
Years in OME	< 5 years	182	29.8
	5–10 years	147	24.1
	11–20 years	157	25.7
	> 20 years	124	20.3
Role Group	Clinical	378	58.5
	Non-clinical	268	41.5

Table 1. Respondent Characteristics

(Note. Gender n = 648; Ethnicity n = 644; Employment n = 645; Years in OME n = 610; Role Group n = 646. Sixty-nine respondents did not provide a professional role. Percentages are of non-missing responses within each characteristic.)

The five institutions with the highest response counts were Rowan-Virtua SOM (*n* = 48), WVSOM (*n* = 47), PCOM (*n* = 41), UNE COM (*n* = 36) and TUNCOM and AZCOM (both *n* = 35). Twenty-eight respondents selected "Other" for their institution, reflecting the open membership of one of the listservs used to distribute the survey (the listserv Society of Osteopathic Medical Educators requires only an interest in osteopathic medical education (OME), not current employment at a COM).

AI Use Frequency and Familiarity

Most respondents reported at least some engagement with AI tools. Among 609 faculty who responded, 32.5% used AI daily and 28.9% weekly, meaning roughly six in ten faculty used AI at least weekly. Another 5.3% used AI monthly and 21.3% had used it a few times. Only 12.0% reported never using AI. Despite this relatively high behavioral engagement, self-rated familiarity told a different story: 56.3% identified as beginners (*n* = 343), 25.5% as intermediate, 11.5% as having no familiarity and just 6.7% as advanced (*n* = 609). This disconnect between use and perceived competence is a defining feature of the current faculty AI landscape and has direct implications for faculty development strategy.

AI Use Frequency	n	%
Daily	198	32.5
Weekly	176	28.9
Monthly	32	5.3
Used it a few times	130	21.3
Never	73	12.0
Total	609	100.0

Table 2. AI use frequency (n = 609).

AI Familiarity	n	%
Advanced	41	6.7
Intermediate	155	25.5
Beginner	343	56.3
No familiarity	70	11.5
Total	609	100.0

Table 3. Self-rated AI familiarity (n = 609).

AI Engagement by Demographics

Gender and AI

There was no statistically significant association between gender and AI use frequency ($\chi^2 = 11.50$, df = 8, $p = .175$, Cramér's $V = 0.097$). However, gender was significantly associated with self-rated AI familiarity ($\chi^2 = 14.30$, df = 6, $p = .026$): men were more likely to rate themselves as advanced (10.3% vs. 3.9% of women), while women were more likely to self-identify as beginners (60.9% vs. 52.2% of men). Whether this reflects genuine differences in technical skill or gendered self-assessment bias—a well-documented phenomenon in STEM fields—cannot be determined from these data but merits attention in faculty development design.

Experience and AI

Years of experience in OME was not significantly associated with AI use frequency ($\chi^2 = 18.71$, df = 12, $p = .096$), though the pattern was suggestive. Faculty with 5–10 years of experience showed the highest rate of daily use (41.5%), while those with more than 20 years had the lowest (30.6%) and the highest rate of never having used AI (17.4%). The lack of statistical significance at conventional thresholds, combined with a moderate test statistic, suggests that career stage effects may be real but modest, consistent with the broader finding in this dataset that individual-level characteristics explain limited variance in AI behaviors.

Clinical vs. Non-Clinical Faculty and AI

Role group (clinical vs. non-clinical) was not significantly associated with AI use frequency ($\chi^2 = 7.70$, df = 4, $p = .103$) or AI familiarity ($\chi^2 = 4.25$, df = 3, $p = .235$). Non-clinical faculty showed a slightly higher proportion of daily users (38.6% vs. 28.4% among clinical faculty), but clinical faculty were more likely to report weekly use (31.7% vs. 25.1%). These differences did not reach significance.

Where the two groups diverged sharply was in *which* AI technologies they used. Among 549 respondents, 32.0% of clinical faculty reported using EHR tools with AI features, compared to only 8.9% of non-clinical faculty ($\chi^2 = 39.06$, $p < .001$). Similarly, telehealth/remote monitoring use was higher among clinical faculty (12.6% vs. 6.2%, $\chi^2 = 5.28$, $p = .022$). In contrast, LLM use was similar across groups (58.8%

clinical vs. 66.1% non-clinical, $p = .101$). These patterns confirm that clinical faculty's AI engagement is more diffused across practice-embedded tools, while non-clinical faculty concentrate their use in LLMs.

Role group was strongly associated with AI policy awareness ($\chi^2 = 27.40$, df = 5, $p < .001$, Cramér's $V = 0.223$), with clinical faculty disproportionately reporting they were "Unsure/Don't know" about their institution's AI policies. This finding aligns with Discovery 3 of the executive summary: Policy communication—not policy existence—is the actionable variable.

AI Technologies in Current Use

Among 549 respondents, LLMs were the dominant technology (61.7%), followed at a distance by EHR tools with AI features (22.6%), telehealth/remote monitoring (10.0%), AI-powered virtual patients (6.9%), simulation analytics (4.9%) and AI-driven assessment/NLP platforms (3.8%). A quarter of respondents (25.1%) reported using no AI technologies at all. The concentration of use in LLMs—with all other categories below 25%—underscores the gap between the breadth of available AI tools and the narrowness of current adoption.

Technology	n	% of Respondents
Large language models (ChatGPT, etc.)	339	61.7
EHR tools with AI features	124	22.6
Telehealth/remote monitoring	55	10.0
AI-powered virtual patients/chatbots	38	6.9
Simulation analytics	27	4.9
AI-driven assessment (NLP)	21	3.8
None currently	138	25.1

Table 4. AI technologies currently used in teaching or clinical education (n = 549). Respondents could select multiple technologies; percentages sum to more than 100%.

Perceptions of AI in Education

Faculty perceptions of AI were generally positive regarding personal efficacy but considerably more skeptical regarding institutional readiness. Two-thirds (67.2%) agreed or strongly agreed that AI tools would improve their effectiveness as educators, and 56.0% believed AI-enabled feedback would benefit students. However, less than a third (30.4%) felt that integrating AI into teaching would be straightforward, and only 34.7% perceived that their colleagues and leadership expected AI adoption.

The sharpest finding concerned institutional capacity: Just 19.1% agreed their institution was using AI effectively, and only 14.5% agreed their institution was "ahead of the curve." Meanwhile, 29.2% expressed concerns about their institution's ability to implement AI properly. Nearly half (48.5%) indicated intention to incorporate AI into their teaching within 12 months, suggesting a faculty body that is more ready than their institutions appear to be.

Perception Item	% Agree/ Strongly Agree	n
AI will improve my effectiveness as an educator	67.2	573
AI feedback/assessment will benefit students	56.0	573
Intend to incorporate AI within 12 months	48.5	569
Easy to learn and operate AI tools	47.5	571
Have institutional support for AI	40.7	568
Colleagues/leadership expect AI adoption	34.7	567
Integrating AI would be straightforward	30.4	569
Concerns about institution's AI implementation	29.2	568
Institution is using AI effectively	19.1	566
Institution is ahead of the curve in AI	14.5	566

Table 5. Faculty perceptions of AI (Q11). Items are sorted by descending agreement.

Faculty Development Needs in AI

Overall Training Needs

Self-reported training needs were elevated across all eight domains, with no domain averaging below the midpoint of the five-point scale (Table 6). The highest-need domains were integrating AI into competency-based assessment and feedback ($M = 3.57$), AI for curriculum design ($M = 3.47$), technical skills ($M = 3.45$), and policy and governance ($M = 3.50$). The lowest-need domain was basic AI concepts ($M = 2.95$), suggesting that faculty perceive themselves as beyond introductory content even when most identify as beginners. The composite training need score across all eight domains was $M = 3.35$ (SD = 0.90, $n = 547$).

Training Domain	M	n
AI in assessment & feedback	3.57	544
Policy & governance	3.50	541
AI for curriculum design	3.47	546
Technical skills	3.45	541
Ethics & professionalism	3.35	545
AI-enabled study tools	3.34	546
EHR data for simulations	3.21	540
Basic AI concepts	2.95	545

Table 6. Mean self-reported training need by domain (1 = No need, 5 = Urgent need). Sorted by descending mean.

Training Needs by AI Use Frequency

AI use frequency was significantly associated with training needs across all eight domains (Kruskal-Wallis $p < .01$ for all). The pattern was consistent and somewhat counterintuitive: Faculty who had never used AI reported the *lowest* training needs across every domain, while those using AI weekly or monthly reported the highest. For example, mean need for training in AI assessment and feedback was 3.79 among weekly users but only 2.80 among non-users. This suggests that exposure to AI *creates* perceived training needs—faculty who have not tried AI may not yet understand what they don't know—and that the heaviest users recognize the gap between their current capacity and the tools' potential.

Training Domain	Daily	Weekly	Monthly	Few Times	Never	p
Basic AI concepts	2.81	3.04	3.13	3.19	2.62	.006
Ethics & professionalism	3.28	3.44	3.48	3.55	2.83	.004
AI-enabled study tools	3.32	3.44	3.65	3.51	2.68	<.001
AI in assessment & feedback	3.62	3.79	3.63	3.52	2.80	<.001
AI for curriculum design	3.53	3.66	3.55	3.50	2.72	<.001
EHR data for simulations	3.42	3.32	3.26	3.16	2.47	<.001
Policy & governance	3.59	3.60	3.71	3.61	2.67	<.001
Technical skills	3.52	3.57	3.74	3.50	2.77	.001

Table 7. Mean training needs by AI use frequency. p values from Kruskal-Wallis H tests.

Training Needs by Years of Experience

Years of experience in OME showed no statistically significant relationship with training needs in any of the eight domains (Kruskal-Wallis $p > .07$ for all). The absence of career-stage differences means that faculty development programs need not be tiered by seniority. There was a slight tendency for faculty with more than 20 years of experience to report somewhat higher need for basic AI concepts ($M = 3.15$) and somewhat lower need for policy and governance ($M = 3.34$) compared to their less experienced peers, but these differences were small and non-significant.

Subgroup Analysis: Clinical and Non-Clinical Faculty

Overall Profile

The sample comprised 378 clinical faculty (58.5%) and 268 non-clinical faculty (41.5%), with 69 respondents unclassifiable due to missing role data. Clinical and non-clinical faculty did not differ significantly in gender composition ($\chi^2 = 1.94$, $p = .379$) or years of experience ($\chi^2 = 3.08$, $p = .380$). Within the clinical group, 352 were clinical physicians and 26 were clinical non-physicians (e.g., PAs, NPs, OTs).

Training Needs: Clinical vs. Non-Clinical

Clinical faculty reported significantly higher training needs than non-clinical faculty in three domains: basic AI concepts (Mann-Whitney $p = .003$), AI-enabled study tools ($p = .013$) and technical skills ($p = .037$). Training needs for EHR data simulations ($p = .049$) and policy and governance ($p = .055$) were marginally higher among clinical faculty. The overall composite training need was higher for clinical faculty ($M = 3.43$, SD = 0.88) than non-clinical faculty ($M = 3.25$, SD = 0.91). No domain showed higher needs among non-clinical faculty.

Training Domain	Clinical M	Non-Clinical M	p
Basic AI concepts	**3.07**	**2.80**	**.003**
Ethics & professionalism	3.40	3.28	.262
AI-enabled study tools	**3.44**	**3.20**	**.013**
AI in assessment & feedback	3.60	3.49	.130
AI for curriculum design	3.49	3.44	.391
EHR data for simulations	**3.32**	**3.06**	**.049**
Policy & governance	3.59	3.37	.055
Technical skills	**3.55**	**3.32**	**.037**

Table 8. Mean training needs by role group. p-values from Mann-Whitney U tests; significant ($p<0.05$) p-values bolded.

Within Clinical Faculty: Physician vs. Non-Physician Clinicians

Among clinical faculty, no significant differences in training needs emerged between clinical physicians ($n = 302$) and clinical non-physician educators ($n = 22$; Mann-Whitney $p > .40$ for all domains). Non-

physician clinicians showed slightly higher means on every domain (e.g., technical skills: *M* = 3.68 vs. 3.54), but the small non-physician sample size limits statistical power and precludes strong conclusions. These results suggest that faculty development content can be designed for clinical faculty as a unified group, with role-specific examples (e.g., EHR-based scenarios for physicians, team-based care simulations for non-physicians) rather than separate curricula.

Training Needs by AI Use Frequency Within Role Groups

Within clinical faculty, AI use frequency was significantly associated with training needs across all eight domains (Kruskal-Wallis $p < .05$ for all). The "Never" group consistently reported the lowest needs. Weekly and monthly users reported the highest needs, with weekly users showing the peak mean for AI in assessment and feedback (*M* = 3.92).

Among non-clinical faculty, this pattern was substantially attenuated. Only two domains reached significance: policy and governance ($p = .034$) and technical skills ($p = .021$). The remaining six domains showed trends in the same direction but did not reach significance ($p = .06$–$.87$). This divergence is important: It suggests that for clinical faculty, any AI exposure—however modest—activates awareness of training gaps, whereas non-clinical faculty (who may already be more embedded in educational technology environments) show a more muted response to variation in use frequency.

Domain	Clinical p	Non-Clinical p
Basic AI concepts	.002	.872
Ethics & professionalism	.031	.197
AI-enabled study tools	.001	.062
AI in assessment & feedback	<.001	.084
AI for curriculum design	<.001	.075
EHR data for simulations	<.001	.139
Policy & governance	.001	.034
Technical skills	.002	.021

Table 9. Kruskal-Wallis p values for training need by AI use frequency, stratified by role group.

Faculty Development Priority Rankings

When asked to rank six faculty development priority areas (1 = highest), foundational AI literacy was the clear first priority (*M* rank = 2.20, *n* = 435), followed by hands-on tool training (*M* = 2.71), AI-enabled assessment and feedback (*M* = 3.53), policy and governance (*M* = 3.90), infrastructure and support (*M* = 4.15) and EHR-driven simulations (*M* = 4.51). Clinical and non-clinical faculty agreed on the top two priorities and showed no significant differences in any area except EHR simulations, which clinical faculty ranked higher (*M* = 4.37 vs. 4.70, $p = .016$). This convergence in priorities, despite differences in training-need intensity, supports a shared faculty development core.

Priority Area	Mean Rank	Clinical	Non-Clinical
Foundational AI literacy	2.20	2.21	2.20
Hands-on tool training	2.71	2.70	2.71
AI assessment & feedback	3.53	3.53	3.53
Policy & governance	3.90	3.92	3.88
Infrastructure & support	4.15	4.27	3.99
EHR-driven simulations	4.51	4.37*	4.70*

*Table 10. Mean priority rankings (lower = higher priority). * p = .016 for clinical vs. non-clinical comparison on EHR simulations. n = 435.*

Institutional AI Policy Awareness

Policy awareness remains a significant gap. Among 549 respondents, 49.5% were "Unsure/Don't know" about their institution's AI policy status, 16.9% reported policies covering both students and faculty, 13.8% indicated policies were being developed, 10.7% reported student-only policies, 8.2% said no policies existed and 0.7% reported faculty-only policies. Clinical faculty were disproportionately unsure, as noted above.

Policy Status	n	%
Unsure/Don't know	272	49.5
Yes—both students and faculty	93	16.9
Policies being developed	76	13.8
Yes—students only	59	10.7
No policies exist	45	8.2
Yes—faculty/administrators only	4	0.7
Total	549	100.0

Table 11. Institutional AI policy awareness (n = 549).

Technology Adoption Propensity and Personal AI Use

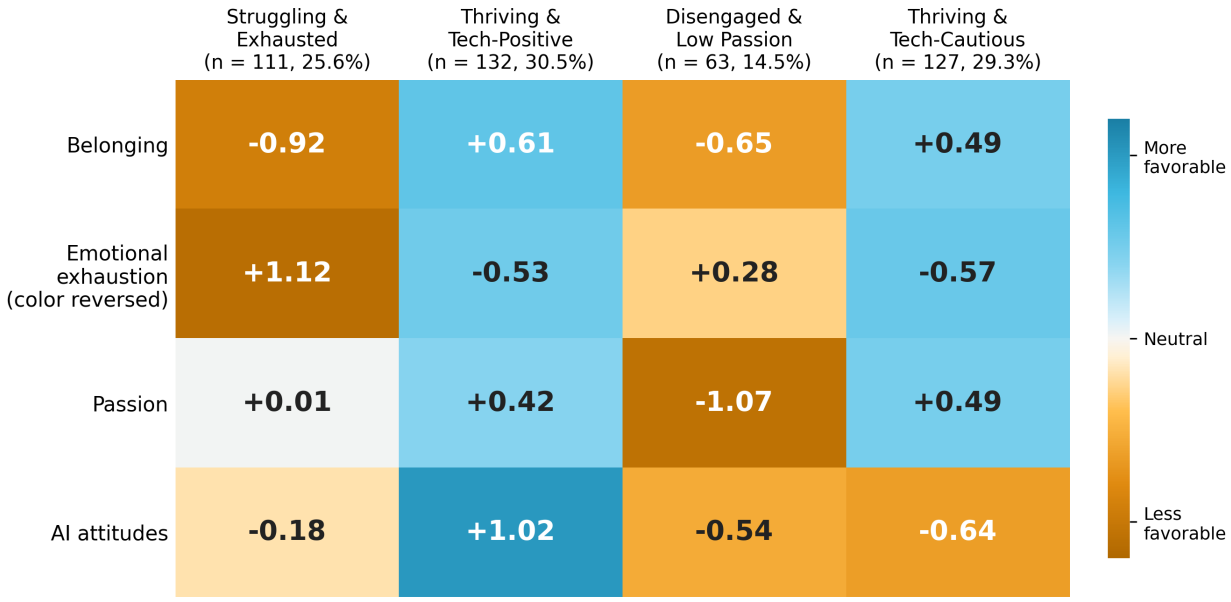
When asked about general technology adoption, 25.7% described themselves as early adopters who actively seek new technologies, 35.6% said they were likely adopters, 25.9% were neutral and 11.4% were unlikely or very unlikely adopters (n = 529). Personal generative AI use mirrored professional patterns: 27.5% used generative AI daily in their personal lives, 28.1% weekly, 5.5% monthly, 20.8% a few times, 5.8% had never used it but would like to and 12.3% had never used it (n = 530). Role group was not significantly associated with technology adoption propensity ($\chi^2 = 2.68$, $p = .612$).

AACOM
American Association of Colleges of Osteopathic Medicine

AI Attitudes, Well-being and Workplace Belonging

To map how AI intersects with well-being and the workplace, a k-means clustering analysis integrated standardized composites of workplace belonging (seven items), emotional exhaustion (five items), passion for work (three items) and an AI attitudes composite (mean of 10 recoded teaching-related AI items, with the single negatively worded item reverse-coded), yielding four interpretable profiles (N=433; ~39.5% listwise deletion): **Struggling and Exhausted** (low belonging, high exhaustion), **Thriving and Tech-Positive** (high belonging, low exhaustion, highest AI attitudes), **Disengaged and Low Passion** (markedly low passion, below-average AI attitudes) and **Thriving and Tech-Cautious** (high belonging, low exhaustion, below-average AI attitudes). All clusters differ strongly on the four composites (all $F>120$, all $p<0.001$; η^2: belonging=0.464, exhaustion=0.515, passion=0.631, AI attitudes=0.484), establishing a robust link between workplace experiences and well-being and revealing that two thriving groups share similarly strong well-being yet diverge sharply in AI attitudes. These profiles demonstrate that high well-being is compatible with either enthusiasm or caution toward AI, whereas distress (Struggling) and disengagement (low passion) coincide with below-average AI attitudes, indicating that workplace climate and well-being are tightly coupled and that AI sentiment is not a simple proxy for well-being status. The heatmap below, Figure 1., shows the direction and strength of the four key variables for each group.

Figure 1. K-means Cluster Analysis Results



Behavioral engagement with AI aligns closely with these profiles. The **Engaged AI Adopters (the thriving, tech-positive group)** report the highest AI use frequency (median weekly to daily) and familiarity, while the **Disengaged Faculty** report significantly lower use frequency and the lowest adoption of key tools: only 41.7% use large language models and 41.7% report using no AI tools at all; specialized educational AI (virtual patients, simulation analytics) is near absent in this group (Kruskal-Wallis for familiarity $H=28.953$, $p<0.0001$); for use frequency ($H=68.324$, $p<0.0001$; LLM $\chi^2(3)=44.77$, $p<0.001$); no tools $\chi^2(3)=45.06$, $p<0.001$). Importantly, the **Disengaged Faculty's** low training needs do not reflect advanced competence:

their familiarity resembles that of the Thriving Traditionalists but their behavior shows markedly lower use indicating active disengagement rather than saturation of skill. Consistent with this, training needs are strikingly uniform across the four profiles: only one of eight domains (Basic AI Concepts) shows a small between-profile difference, while priority domains such as AI-enabled assessment, curriculum design, policy/governance and technical skills are elevated across all groups; overall intensity is highest among those struggling and lowest among the disengaged (Kruskal-Wallis across domains largely non-significant; for Basic AI Concepts $H=8.74$, $p=0.033$; all effects small) but demographic subgroup analyses beyond role and career stage are limited by small cell sizes and missingness, warranting cautious interpretation; follow-up studies to test moderation by gender and race with adequate power and appropriate clustering by institution are recommended.

Discussion

Generative AI is diffusing rapidly into higher education, raising urgent questions about how faculty are using these tools, what development they need and how AI intersects with faculty well-being and workplace climate. In medical education, where teaching, clinical demands and curricular oversight co-exist, the stakes for effective technology adoption are high, yet adoption can be experienced as either energizing or burdensome. Understanding whether attitudes toward AI or actual use better predict well-being and how institutional belonging shapes these attitudes and needs, can inform targeted support that enhances professional thriving without exacerbating burnout.

No meaningful differences in training needs exist across any demographic groups, nor do Clinical and non-clinical Faculty report widely differing needs. Only a small variation in one educational domain (Basic AI Education) was found to be associated with faculty experience in OME Across osteopathic medical school faculty, more positive attitudes toward AI consistently aligned with higher professional passion and better facets of well-being, independent of how often faculty actually use AI. Workplace belonging relates to more favorable AI attitudes and greater stated AI training needs, and the link between belonging and passion is partially mediated by AI attitudes; AI engagement itself shows no as-sociation with emotional exhaustion, and any link between training needs and exhaustion is marginal and practically negligible.

In addition to offering support to faculty through faculty development (specifically in foundational AI literacy and hands-on tool training), AACOM and others should consider supporting COMs to clarify AI policies in order to allow greater clarity among faculty which will encourage AI education and use.

AACOM
American Association of Colleges of Osteopathic Medicine

Appendix A. Faculty AI Development Needs and Well-being Survey

FacultySurvey_Fall2025_Well-being_AINeeds

Survey Flow
Block: Introduction and Consent (1 Question)
Standard: Profile (6 Questions)
Standard: Prior Exposure to Digital Health (2 Questions)
Standard: Perceptions of Technology (1 Question)
Standard: Current Practices and Needs (4 Questions)
Standard: Institutional Environment & Policy (3 Questions)
Standard: Priority-Setting (2 Questions)
Standard: Technology Adoption (2 Questions)
Standard: CBME (8 Questions)
Standard: Workplace Environment (8 Questions)

AACOM
American Association of Colleges of Osteopathic Medicine

Start of Block: Introduction and Consent

Welcome! AACOM is surveying COM faculty and preceptors to understand faculty well-being and the workplace factors that shape it, as well as one of the key forces set to change education: artificial intelligence (AI). This anonymous survey has four sections: first, a section on your professional development needs around artificial intelligence (AI) and related digital health technology; second, a brief section on Competency-Based Education (CBE) efforts at your College of Osteopathic Medicine (COM); third, a section to find out more about you and your role at your COM; and finally, a section on your workplace and your workplace environment. Your feedback is vital in helping us support faculty across all COMs as we try and develop shared and sharable targeted resources, training, and model policies for your school, your students, and you. Your participation is voluntary and anonymous and all results will be reported in aggregate, with COM-level summaries only when at least five responses are available. No names or emails are collected. The survey takes 20-25 minutes. You may skip any question or stop at any time. For questions, contact mspeicher@aacom.org. By selecting 'I agree,' you consent to participate and to allow us to use your data in this survey and subsequent reports and analyses.

End of Block: Introduction and Consent

Start of Block: Profile

How do you describe your gender identity?

- ○ Male/man (1)
- ○ Female/woman (2)
- ○ Trans male/trans man (3)
- ○ Trans female/trans woman (4)
- ○ Genderqueer/gender non-conforming (5)
- ○ I prefer to self-describe: (6) _____
- ○ I prefer to not respond. (7)

AACOM
American Association of Colleges of Osteopathic Medicine

How do you describe your race or ethnicity (Select all that apply)?

- [ ] American Indian or Alaskan Native (1)
- [ ] Asian (2)
- [ ] Black or African-American (3)
- [ ] Hispanic or Latino (4)
- [ ] Native Hawaiian or Other Pacific Islander (5)
- [ ] White (6)
- [ ] I prefer to not respond. (7)

Primary professional role (Select all that apply)

- [ ] COM faculty—basic science (1)
- [ ] COM faculty—clinical (physician) (2)
- [ ] COM faculty—clinical (non-physician, e.g., PA, NP, OT) (3)
- [ ] Simulation or skills lab educator (4)
- [ ] Clerkship/course director or program administrator (5)
- [ ] Curriculum developer or educational researcher (6)
- [ ] Other (please specify): (7) _____

Full-time or part-time status

- ○ Full-time (1)

○ Part-time (2)

AACOM
American Association of Colleges of Osteopathic Medicine

Years of experience in osteopathic medical education

- ◯ < 5 years (1)
- ◯ 5 -- 10 years (2)
- ◯ 11 -- 20 years (3)
- ◯ > 20 years (4)

What institution are you affiliated with?

- ◯ ACOM (1)
- ◯ ARCOM (4)
- ◯ ATSU-KCOM (5)
- ◯ ATSU-SOMA (6)
- ◯ AZCOM (7)
- ◯ BCOM - FIT (8)
- ◯ BUCOM (9)
- ◯ Burrell COM (10)
- ◯ CCOM (11)
- ◯ CHSU-COM (12)
- ◯ CUSOM (13)
- ◯ DCOM at LMU-Knoxville (14)
- ◯ DMU-COM (15)
- ◯ DUQCOM (16)
- ◯ ICOM (17)
- ◯ KCU-Joplin (18)
- ◯ KCU-Kansas (19)

- ○ KHSU-KansasCOM (20)
- ○ LECOM (21)
- ○ LECOM Bradenton (22)
- ○ LECOM Elmira (23)
- ○ LECOM Seton Hill (24)
- ○ LMU-DCOM (25)
- ○ LUCOM (26)
- ○ MCOM (27)
- ○ MSOM (28)
- ○ MSUCOM (29)
- ○ MSUCOM Clinton Township (30)
- ○ MSUCOM Detroit (31)
- ○ MU-WCOM (32)
- ○ Noorda COM (33)
- ○ NSU-KPCOM (34)
- ○ NSU-KPCOM Clearwater (35)
- ○ NYITCOM at Arkansas State (36)
- ○ NYITCOM Long Island (37)
- ○ OCOM (38)
- ○ OSU-COM (39)
- ○ OSUCOM Tahlequah (40)
- ○ OU-HCOM (41)
- ○ OU-HCOM Cleveland (42)

- ○ OU-HCOM Dublin (43)
- ○ PCOM (44)
- ○ PCOM Georgia (45)
- ○ PCOM South Georgia (46)
- ○ PNWU-COM (47)
- ○ Rowan-Virtua SOM (48)
- ○ Rowan-Virtua SOM Sewell (49)
- ○ RVUCOM (50)
- ○ RVUCOM Southern Utah (51)
- ○ SHSU-COM (52)
- ○ TouroCOM-Harlem (53)
- ○ TouroCOM-Middletown (54)
- ○ TouroCOM-Montana (55)
- ○ TUCOM-CA (56)
- ○ TUNCOM (57)
- ○ UIWSOM (58)
- ○ UNE COM (59)
- ○ UNTHSC/TCOM (60)
- ○ UP-KYCOM (61)
- ○ VCOM-Auburn (62)
- ○ VCOM-Carolinas (63)
- ○ VCOM-Louisiana (64)
- ○ VCOM-Virginia (65)

- ○ WCUCOM (66)
- ○ WesternU/COMP (67)
- ○ WesternU/COMP-Northwest (68)
- ○ WVSOM (69)
- ○ OTHER (3) _____

End of Block: Profile

Start of Block: Prior Exposure to Digital Health

How often do you personally use AI tools (e.g., ChatGPT, Copilot)?

- ○ Daily (1)
- ○ Weekly (2)
- ○ Monthly (3)
- ○ I've used it a few times (4)
- ○ Never (5)

How would you rate your familiarity with AI/digital health concepts?

- ○ No familiarity (1)
- ○ Beginner (2)
- ○ Intermediate (3)
- ○ Advanced (4)

End of Block: Prior Exposure to Digital Health

AACOM
American Association of Colleges of Osteopathic Medicine

Start of Block: Perceptions of Technology

Q11 Perceptions of technology

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
AI tools will improve my effectiveness as an educator. (1)	○	○	○	○	○
AI-enabled feedback or assessment will benefit my students. (2)	○	○	○	○	○
I find it easy to learn and operate AI tools in my workflow. (3)	○	○	○	○	○
Integrating AI into teaching and administration would be straightforward. (4)	○	○	○	○	○
My colleagues and leadership expect faculty to adopt AI/digital technologies. (5)	○	○	○	○	○
I have access to institutional support (training,	○	○	○	○	○

IT) for using AI tools. (6)					
I intend to incorporate AI tools into my teaching or assessment within 12 months. (7)	○	○	○	○	○
My institution is using AI effectively. (8)	○	○	○	○	○
My institution is ahead of the curve in leveraging data and AI. (9)	○	○	○	○	○
I have concerns about my institution's ability to implement and use AI properly. (10)	○	○	○	○	○

End of Block: Perceptions of Technology

Start of Block: Current Practices and Needs

Q12 Which AI/digital health technologies do you currently use in teaching or clinical education (Select all that apply)?

- ☐ Large language models (ChatGPT, Bard, etc.) (1)
- ☐ AI-powered virtual patients or chatbots (2)
- ☐ Simulation analytics (motion tracking, automated scoring) (3)

- [ ] AI-driven assessment platforms (NLP feedback) (4)
- [ ] Electronic Health Record (EHR) tools with AI features (smart alerts, documentation aids) (5)
- [ ] Telehealth/remote monitoring (6)
- [ ] None currently (7)
- [ ] Other(s) (specify): _____ (8)

Rate your need for training or resources in each of the following domains

	No need for training (1)	Little need for training (2)	Some need for training (3)	Great need for training (4)	Urgent need for training (5)
Basic AI concepts and terminology (1)	○	○	○	○	○
Ethical and professionalism challenges (e.g., AI-assisted cheating) (2)	○	○	○	○	○
Developing and using AI-enabled study tools (flashcards, chatbots) (3)	○	○	○	○	○
Integrating AI into competency-based assessment and feedback (4)	○	○	○	○	○
Using AI tools for curriculum design and content creation (5)	○	○	○	○	○

Leveraging EHR data for educational simulations (6)	○	○	○	○	○
Policy development and governance for AI use (7)	○	○	○	○	○
Technical skills: operating and troubleshooting AI systems (8)	○	○	○	○	○

What barriers do you face in adopting AI/digital technologies? (e.g., time, technical, cultural)
[TEXT BLOCK]

What support or resources would most help you integrate AI into your work?
[TEXT BLOCK]

End of Block: Current Practices and Needs

Start of Block: Institutional Environment & Policy

Does your COM currently have formal policies addressing AI use by faculty or students?

- ○ Yes—students only (1)
- ○ Yes—faculty/administrators only (2)
- ○ Yes—both students and faculty (3)
- ○ Policies for some or all groups are being developed (4)
- ○ No (5)
- ○ Unsure/Don't know (6)

Display this question:

Does your COM currently have formal policies addressing AI use by faculty or students? = Policies for some or all groups are being developed
Or Does your COM currently have formal policies addressing AI use by faculty or students? = No

Indicate your COM's status for developing AI policies

	Not started (1)	Discussion (2)	Development group established (3)	Policy(ies) drafted (4)	Policy approved (5)
Student policies (1)	○	○	○	○	○
Faculty/Administration policies (2)	○	○	○	○	○
Other policies (3)	○	○	○	○	○

In your view, what policy element(s) are essential to guide AI use in osteopathic medical education?
[TEXT BLOCK]

End of Block: Institutional Environment & Policy

Start of Block: Priority-Setting

Please rank the following areas (where 1 is the highest priority) to help guide AACOM's immediate focus on faculty development
_____ Foundational AI literacy (concepts, ethics) (1)
_____ Hands-on tool training (LLMs, simulation analytics) (2)
_____ AI-enabled assessment and feedback methods (3)
_____ EHR-driven educational simulations (4)
_____ Policy and governance frameworks (5)
_____ Infrastructure and technical support (6)

Any additional comments or suggestions for AACOM's AI faculty development initiatives?
[TEXT BLOCK]

End of Block: Priority-Setting

Start of Block: Technology Adoption

In general, how likely are you to adopt the newest digital technologies in your personal life?

- ○ Very likely, I actively seek out new technologies and am usually one of the early adopters (1)
- ○ Likely (2)
- ○ Neutral, I may consider adopting new technologies, but tend to wait until others have adopted them (3)
- ○ Unlikely (4)
- ○ Very unlikely, I rarely adopt new technologies soon after they come out and prefer to use what I am familiar with (5)

How often do you currently use generative AI solutions (e.g., ChatGPT, Gemini, Microsoft Copilot) in your personal life?

- ○ Daily (1)
- ○ Weekly (2)
- ○ Monthly (3)
- ○ A few times (4)
- ○ Never, but I'd like to try them (5)
- ○ Never (6)

End of Block: Technology Adoption

Start of Block: Workplace Environment

Please respond to each statement below, describing how you usually feel (from Strongly Disagree to Strongly Agree):

	Strongly disagree (1)	Disagree (2)	Slightly disagree (3)	Neither agree nor disagree (4)	Slightly agree (5)	Agree (6)	Strongly agree (7)
I feel joy in a typical workday. (1)	○	○	○	○	○	○	○
Overall, I feel	○	○	○	○	○	○	○

enthusiastic about my work. (2)							
I love my job. (3)	○	○	○	○	○	○	○
I typically become absorbed while I am working on something that challenges my abilities. (4)	○	○	○	○	○	○	○
I lose track of time while doing something I enjoy at work. (5)	○	○	○	○	○	○	○
When I am working on something I enjoy, I forget everything else around me. (6)	○	○	○	○	○	○	○
I can receive support from coworkers if I need it. (7)	○	○	○	○	○	○	○
I feel appreciated by my coworkers. (8)	○	○	○	○	○	○	○

I trust my colleagues. (9)	○	○	○	○	○	○	○
My colleagues bring out my best self. (10)	○	○	○	○	○	○	○
My work is meaningful. (11)	○	○	○	○	○	○	○
I understand what makes my job meaningful. (12)	○	○	○	○	○	○	○
The work I do serves a greater purpose. (13)	○	○	○	○	○	○	○
I set goals that help me achieve my career aspirations. (14)	○	○	○	○	○	○	○
I typically accomplish what I set out to do in my job. (15)	○	○	○	○	○	○	○
I am generally satisfied with my performance at work. (16)	○	○	○	○	○	○	○
I typically feel	○	○	○	○	○	○	○

physically healthy. (17)							
I am rarely sick. (18)	○	○	○	○	○	○	○
I can typically overcome sources of physical distress (e.g., insomnia, injuries, and vision issues). (19)	○	○	○	○	○	○	○
I feel in control of my physical health. (20)	○	○	○	○	○	○	○
I believe I can improve my job skills through hard work. (21)	○	○	○	○	○	○	○
I believe my job will allow me to develop in the future. (22)	○	○	○	○	○	○	○
I have a bright future at my current work organization. (23)	○	○	○	○	○	○	○
My physical work environment (e.g., office space)	○	○	○	○	○	○	○

allows me to focus on my work. (24)							
There is plenty of natural light in my workplace. (25)	○	○	○	○	○	○	○
I can conveniently access nature in my work environment (e.g., parks, oceans, and mountains). (26)	○	○	○	○	○	○	○
I am comfortable with my current income. (27)	○	○	○	○	○	○	○
I could lose several months of pay due to serious illness and still have my economic security. (28)	○	○	○	○	○	○	○
In the event of a financial emergency, I have adequate savings. (29)	○	○	○	○	○	○	○

Please complete the following statements:

AACOM
American Association of Colleges of Osteopathic Medicine

	Poor (1)	Marginal (2)	Satisfactory (3)	Good (4)	Optimal (5)
The degree to which my team works efficiently together is: (1)	○	○	○	○	○
My control over my workload is: (2)	○	○	○	○	○

How likely would you be to recommend your COM as a place to work, to a friend or colleague?

- ○ 0 - Not at all likely (1)
- ○ 1 (3)
- ○ 2 (4)
- ○ 3 (5)
- ○ 4 (6)
- ○ 5 (7)
- ○ 6 (8)
- ○ 7 (9)
- ○ 8 (10)
- ○ 9 (11)
- ○ 10 - Extremely likely (12)

Overall, based on your own definition of burnout, how would you rate your level of burnout?

- ○ I enjoy my work. I have no symptoms of burnout. (1)
- ○ Occasionally I am under stress, and I don't have as much energy as I once did, but I don't feel burned out. (2)
- ○ I am definitely burning out and have one or more symptoms of burnout, such as physical or emotional exhaustion. (3)

○ The symptoms of burnout that I am experiencing won't go away. I think about frustration at work alot. (4)

○ I feel completely burned out and often wonder if I can go on. I am at the point where I may need some changes or may need to seek some sort of help. (5)

Please respond to each statement below, describing how you usually feel (from 1 = do not agree at all; to 7 = very strongly agree):

	1 (Do not agree at all) (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (Very strongly agree) (7)
I spend a lot of time doing my job as a medical educator. (1)	○	○	○	○	○	○	○
I like my job as a medical educator. (2)	○	○	○	○	○	○	○
My job as a medical educator is important for me. (3)	○	○	○	○	○	○	○
My job as a medical educator is a passion for me. (4)	○	○	○	○	○	○	○

AACOM
American Association of Colleges of Osteopathic Medicine

Please respond to each statement below, describing how you usually feel (from disagree strongly to agree strongly):

	Disagree strongly (1)	Disagree slightly (2)	Neutral (3)	Agree slightly (4)	Agree strongly (5)
Events in this work setting affect my life in an emotionally unhealthy way. (1)	○	○	○	○	○
I feel burned out from my work. (2)	○	○	○	○	○
I feel fatigued when I get up in the morning and have to face another day on the job. (3)	○	○	○	○	○
I feel frustrated by my job. (4)	○	○	○	○	○
I feel I am working too hard on my job. (5)	○	○	○	○	○

Please respond to each statement below, describing how you usually feel (from 1 = strongly disagree to 6 = strongly agree):

	1 = Strongly disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 = Stronly agree (6)
I feel like this medical school is a good fit for me. (1)	○	○	○	○	○	○
I feel like I belong at my COM. (2)	○	○	○	○	○	○

I feel respected at my COM. (3)	○	○	○	○	○	○
My COM supports professional development to improve our teaching. (4)	○	○	○	○	○	○
My COM values us getting better at our teaching. (5)	○	○	○	○	○	○
My COM provides us time and resources to get better at our teaching. (6)	○	○	○	○	○	○
Overall, I am satisfied with my current job. (7)	○	○	○	○	○	○

How likely is it that you will actively look for a job in the next year?

- ○ Extremely unlikely (1)
- ○ Somewhat unlikely (2)
- ○ Unlikely (3)
- ○ Somewhat likely (4)
- ○ Likely (5)
- ○ Extremely likely (6)

End of Block: Workplace Environment

AACOM
American Association of Colleges of Osteopathic Medicine

End of Survey