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# Drivers of sustainable biomedical waste management practices among healthcare workers in Bangladesh: a cross-sectional structural equation modelling study

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## Abstract

# Background

Sustainable biomedical waste management protects healthcare workers, patients, communities, and the environment. Appropriate practice depends not only on knowledge and attitudes but also on behavioural intention, perceived control, organisational support, and regulatory awareness. This study examined the drivers of sustainable biomedical waste-management practices among healthcare workers in Bangladesh using an extended theory of planned behaviour framework.

# Methods

A cross-sectional, facility-based survey was conducted in Dhaka, Bangladesh, between May and September 2026 among 420 healthcare workers from 5 public hospitals, 10 private hospitals, and 13 specialised or diagnostic facilities. A questionnaire with five-point Likert-scale items measured six antecedent constructs, behavioural intention, and sustainable practice. Partial least squares structural equation modelling (SmartPLS 4.1.2.1) was used, with bootstrapping, PLSpredict, measurement invariance of composites testing, and permutation-based multigroup analysis.

# Results

The model explained 41.4% of the variance in behavioural intention and 46.8% in sustainable practice. All six antecedents significantly predicted intention; perceived behavioural control was strongest ($\beta = 0.277$, $p < 0.001$), followed by training and organisational support ($\beta = 0.227$), regulatory awareness ($\beta = 0.219$), knowledge ($\beta = 0.204$), attitude ($\beta = 0.159$), and subjective norms ($\beta = 0.087$, $p = 0.021$). Behavioural intention was the strongest predictor of practice ($\beta = 0.465$, $p < 0.001$), followed by perceived behavioural control ($\beta = 0.247$, $p < 0.001$) and training and organisational support ($\beta = 0.118$, $p = 0.005$). Regulatory awareness had no significant direct effect on practice ($\beta = 0.062$, $p = 0.110$) but a significant indirect effect through intention. PLSpredict indicated meaningful out-of-sample predictive performance. No significant structural-path differences were detected across facility types.

# Conclusions

Sustainable practice appears to be shaped by both motivational and enabling factors. Behavioural intention was the strongest predictor of practice, while perceived behavioural control and organisational support had important direct and indirect roles. Interventions should move beyond knowledge-based training and strengthen workers' ability to act through supportive organisational systems, adequate resources, and effective implementation of regulatory requirements.

# Background

Biomedical waste management is a critical component of safe and sustainable healthcare delivery. Healthcare facilities generate general and hazardous waste streams that can include infectious materials, sharps, pharmaceuticals, chemicals, and other potentially harmful residues. Inadequate segregation, handling, transport, treatment, or disposal can expose healthcare workers, patients, waste handlers, communities, and ecosystems to avoidable risks [1–4]. Healthcare waste management also has a broader sustainability dimension because inappropriate treatment and disposal can contribute to air, soil, and water pollution, greenhouse-gas emissions, resource loss, and unnecessary consumption of single-use materials [5–7].

The challenge is particularly important in low- and middle-income countries, where rapid expansion of health services may occur alongside shortages of waste-treatment infrastructure, uneven staff training, limited occupational protection, and variable regulatory enforcement [2,8–12]. Bangladesh has experienced substantial growth in public, private, specialised, and diagnostic healthcare services, especially in large urban areas such as Dhaka. National rules provide a legal basis for medical-waste management, yet implementation depends on facility-level systems and the routine behaviour of healthcare workers [13]. Previous studies from Bangladesh and comparable settings have reported gaps in segregation, knowledge, training, protective practices, and institutional waste-management capacity [14–19].

Much of the biomedical-waste literature has used knowledge-attitude-practice approaches to describe what healthcare workers know, believe, and report doing [19,20]. Although useful, such studies may not fully explain how individual knowledge and attitudes become sustained behaviour. Healthcare workers may understand appropriate procedures but still face insufficient supplies, inadequate segregation points, time pressure, weak supervision, or uncertainty about institutional and regulatory responsibilities. Conversely, supportive organisational environments can facilitate good practice even when individual motivation varies. A behavioural framework that incorporates individual, social, organisational, and regulatory influences may therefore provide a more informative explanation.

The theory of planned behaviour (TPB) offers such a framework. Ajzen proposed that behavioural intention is an important proximal determinant of behaviour and is shaped by attitude, subjective norms, and perceived behavioural control [21,22]. Attitude reflects a favourable or unfavourable evaluation of the behaviour; subjective norms represent perceived expectations from relevant others; and perceived behavioural control captures the perceived feasibility and controllability of performing the behaviour. TPB has been applied widely to health, environmental, occupational, recycling, and pro-environmental behaviours [23–28].

Biomedical waste management, however, occurs within highly structured organisational environments. Correct segregation, safe sharps disposal, use of protective equipment, and reduction of unnecessary single-use materials depend not only on motivation but also on training, supplies, supervision, infrastructure, and managerial support. Organisational support can strengthen both the intention to

follow appropriate procedures and the practical ability to perform them [29–33]. Regulatory awareness may also influence whether workers understand formal requirements, responsibilities, and consequences associated with waste-management practice [13,34,35].

Knowledge can function as an additional antecedent of intention by helping workers understand the hazards associated with unsafe disposal and the procedures needed for safe management. Yet knowledge is unlikely to operate independently of attitude, social expectations, perceived control, and organisational conditions [19,20,36]. Examining these determinants simultaneously may therefore help identify which factors are most important for behavioural intention and which remain influential after intention is taken into account.

Another limitation of the existing literature is that biomedical-waste determinants are often analysed as separate correlates rather than as components of an interconnected behavioural process. This makes it difficult to determine whether knowledge, organisational support, or regulatory awareness influences practice directly or primarily through behavioural intention. Mediation analysis can clarify these pathways, while predictive assessment can determine whether a model performs beyond in-sample explanation [37–40]. Differences between public, private, and specialised healthcare settings also warrant consideration because organisational structure, resources, workload, and implementation systems may vary across facility types.

Despite the importance of these interconnected influences, evidence integrating individual, social, organisational, and regulatory determinants of sustainable biomedical waste management among healthcare workers in Bangladesh remains limited. The present study therefore examined the drivers of sustainable biomedical waste-management practices among healthcare workers in Dhaka using an extended TPB framework. Knowledge, attitude, subjective norms, perceived behavioural control, training and organisational support, and regulatory awareness were modelled as antecedents of behavioural intention. Behavioural intention, perceived behavioural control, training and organisational support, and regulatory awareness were then examined as predictors of sustainable practice. The study further assessed indirect pathways through behavioural intention, out-of-sample predictive performance, and potential differences across public, private, and specialised or diagnostic healthcare facilities.

## Methods

# Study design and setting

The aim of this study was to examine the drivers of sustainable biomedical waste-management practices among healthcare workers in Bangladesh using an extended theory of planned behaviour model. A cross-sectional, facility-based survey was conducted in Dhaka, Bangladesh, between May and September 2026. Data were collected from 28 healthcare facilities, including 5 public hospitals, 10 private hospitals, and 13 specialised or diagnostic facilities. The study was reported in accordance with

the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) recommendations for cross-sectional studies [41].

## Participants and sampling

The study included healthcare workers who handled or supervised biomedical waste as part of their routine professional responsibilities. Eligible participants included doctors, nurses, medical technologists, and cleaners or waste handlers. Participants were required to have worked in their current role for at least six months and to provide consent to participate.

Healthcare facilities were selected from public, private, and specialised or diagnostic sectors in Dhaka on the basis of accessibility and willingness to participate. Within participating facilities, recruitment was organised across both facility type and staff category to ensure representation of the principal occupational groups involved in biomedical waste management. Eligible healthcare workers present during the data-collection period were approached and invited to participate. A total of 420 complete responses were included in the final analysis. The number of eligible workers who declined participation was not systematically recorded; therefore, a formal response rate could not be calculated.

The minimum required sample size was initially estimated using Cochran's formula, assuming a 95% confidence level, a population proportion of 0.50, and a 5% margin of error [42]. This produced a minimum sample requirement of 384 participants. An allowance for potential non-response was considered during recruitment. Sample adequacy for the structural model was additionally assessed using G*Power [43]. Assuming six predictors, a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and statistical power of 0.80, the estimated minimum requirement was approximately 98 respondents. The final sample of 420 therefore exceeded both the Cochran-based requirement and the minimum estimated for the structural model.

## Study instrument

Data were collected using a structured, self-administered questionnaire available in Bangla and English. Part A collected age, sex, professional role, years of experience in the current role, type of healthcare facility, and previous formal training in biomedical waste management. Part B contained 25 items measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement framework was based on the theory of planned behaviour and extended to incorporate organisational and regulatory determinants [21,22].

Eight reflective constructs were measured. Knowledge, attitude, subjective norms, perceived behavioural control, training and organisational support, and regulatory awareness were each assessed using three items. Behavioural intention was assessed using three items, whereas sustainable biomedical waste-management practice was measured using four items addressing segregation at the point of generation,

safe disposal of sharps, use of appropriate protective equipment, and avoidance of unnecessary single-use materials.

The initial instrument was reviewed by three experts with relevant expertise in public health, healthcare waste management, research methodology, and/or behavioural sciences. The revised questionnaire was then pilot-tested among 40 healthcare workers who were not included in the final analytical sample. The pilot focused on item clarity, comprehension, completion time, and overall feasibility. Minor wording and formatting changes were made before the main survey.

## Data collection

Data were collected by trained members of the research team using both paper-based and electronic versions of the questionnaire. Eligible healthcare workers were approached at their respective facilities, informed about the purpose of the study, and invited to participate voluntarily. No names, employee identification numbers, telephone numbers, or other directly identifying information were collected. Completed questionnaires were stored securely and were accessible only to members of the research team. Responses were checked for completeness before data analysis. The final analytical dataset contained no missing values.

## Ethical considerations

The study was approved by the Ethical Review Committee of Manabik Shahajya Sangstha (MSS) (reference no. MSS-ERC-SFP-R-43/2026; approval date 15 February 2026). All participants were informed about the purpose of the research before participation. Participation was voluntary, and informed consent was obtained before completion of the questionnaire. No directly identifying personal information was collected.

# Statistical analysis

Participant characteristics were summarised using frequencies and percentages for categorical variables and means with standard deviations for continuous variables. The hypothesised model was examined using partial least squares structural equation modelling (PLS-SEM) in SmartPLS version 4.1.2.1 [44]. PLS-SEM was selected because the study aimed to examine a model involving multiple latent constructs, mediation pathways, and prediction of sustainable biomedical waste-management practice. The approach is suitable for models with relatively few indicators per construct and does not require multivariate normality for inference based on non-parametric bootstrapping [37,45].

All constructs were specified as reflective. Knowledge, attitude, subjective norms, perceived behavioural control, training and organisational support, and regulatory awareness were specified as predictors of behavioural intention. Behavioural intention, perceived behavioural control, training and organisational support, and regulatory awareness were specified as predictors of sustainable biomedical waste-

management practice. Model estimation used the path-weighting scheme with a maximum of 3,000 iterations and a stopping criterion of $10^{-7}$. Statistical significance was assessed using non-parametric bootstrapping with 5,000 subsamples, percentile confidence intervals, a two-tailed significance level of $\alpha = 0.05$, and a fixed bootstrap seed of 12345.

## Measurement model assessment

The measurement model was evaluated before the structural relationships. Indicator reliability was assessed using outer loadings, with values of approximately 0.70 or higher considered satisfactory. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability, with values between 0.70 and 0.95 considered acceptable. Convergent validity was assessed using average variance extracted (AVE), with values of at least 0.50 considered adequate. Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT), using a bootstrapped upper confidence bound below 0.85 as the criterion [46].

## Structural model assessment

Collinearity among predictor constructs was examined using inner variance inflation factors (VIF), with values below 3 considered acceptable. Full-collinearity VIFs were additionally examined as a diagnostic for potential common-method bias, using 3.3 as the reference threshold [47]. The structural model was evaluated using standardised path coefficients (β), bootstrapped confidence intervals, p-values, coefficients of determination ($R^2$), and effect sizes ($f^2$). Effect sizes were interpreted using conventional thresholds of approximately 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively [37,45]. Specific indirect, direct, and total effects were examined using bootstrapped confidence intervals. Mediation terminology was applied only where both the relevant indirect and direct pathways were estimated.

# Predictive assessment

Out-of-sample predictive performance was evaluated using PLSpredict with 10 folds and 10 repetitions. Predictive relevance was assessed using $Q^2_predict$ values, and root mean square error (RMSE) values from the PLS-SEM model were compared with those obtained from a linear-model benchmark [39].

# Measurement invariance and multigroup analysis

Potential differences in structural relationships across public, private, and specialised or diagnostic healthcare facilities were assessed using multigroup analysis. Measurement invariance was examined before group comparison using the measurement invariance of composites (MICOM) procedure [48]. Partial measurement invariance was considered sufficient for structural comparisons where the required MICOM conditions were met. Differences in path coefficients between facility groups were assessed using a permutation-based multigroup procedure with 1,000 permutations and two-tailed significance

testing. Comparisons involving constructs that did not establish the required level of measurement invariance were interpreted cautiously.

# Use of generative artificial intelligence

Generative artificial intelligence tools were used to support language editing and the organisation of the manuscript text. They were not used for data collection or for the statistical analysis, which was conducted by the authors in SmartPLS. All authors reviewed the AI-assisted text and verified the scientific content and interpretation of the results.

## Results

# Participant characteristics

A total of 420 healthcare workers were included in the analysis. Of these, 195 (46.4%) worked in public hospitals, 148 (35.2%) in private hospitals, and 77 (18.3%) in specialised or diagnostic facilities. The mean age of participants was 33.6 years (SD 7.9; range 22–59), and the mean duration of experience in their current role was 7.8 years (SD 5.1). Doctors represented the largest occupational group (33.6%), followed by nurses (31.4%), medical technologists (19.0%), and cleaners or waste handlers (16.0%). Overall, 237 participants (56.4%) reported having received formal training in biomedical waste management. No missing data were present in the final analytical dataset.

Table 1
Characteristics of healthcare workers

| Characteristic | n (%) or mean (SD) |
|---|---|
| Age, years | 33.6 (7.9) |
| Experience in current role, years | 7.8 (5.1) |
| Male | 216 (51.4) |
| Female | 203 (48.3) |
| Other | 1 (0.2) |
| Doctor | 141 (33.6) |
| Nurse | 132 (31.4) |
| Medical technologist | 80 (19.0) |
| Cleaner or waste handler | 67 (16.0) |
| Public facility | 195 (46.4) |
| Private facility | 148 (35.2) |
| Specialised or diagnostic facility | 77 (18.3) |
| Formal biomedical waste training: yes | 237 (56.4) |
| Formal biomedical waste training: no | 183 (43.6) |

# Measurement model

Mean construct scores ranged from 3.04 for perceived behavioural control to 3.20 for knowledge. All indicator loadings exceeded 0.70, ranging from 0.762 to 0.891. Cronbach's alpha values ranged from 0.787 to 0.841, composite reliability values from 0.875 to 0.902, and AVE from 0.678 to 0.754. The highest HTMT value was 0.761 for behavioural intention and sustainable biomedical waste practice, and the corresponding bootstrapped 95% upper confidence bound was 0.814. Inner VIF values did not exceed 1.49. Full-collinearity VIF values were also low, with a maximum of 2.04, providing no indication of problematic collinearity or substantial common-method bias under the applied criterion.

Table 2
Measurement model: descriptive statistics, reliability and convergent validity

| Construct | Items | Mean (SD) | Loadings | α | CR | AVE |
|---|---|---|---|---|---|---|
| Knowledge (KN) | 3 | 3.20 (1.06) | 0.863–0.873 | 0.837 | 0.902 | 0.754 |
| Attitude (AT) | 3 | 3.16 (1.05) | 0.845–0.862 | 0.811 | 0.888 | 0.726 |
| Subjective norms (SN) | 3 | 3.14 (1.02) | 0.794–0.891 | 0.800 | 0.881 | 0.711 |
| Perceived behavioural control (PC) | 3 | 3.04 (1.01) | 0.831–0.843 | 0.787 | 0.875 | 0.700 |
| Training and organisational support (OS) | 3 | 3.12 (1.02) | 0.830–0.854 | 0.790 | 0.877 | 0.705 |
| Regulatory awareness (RA) | 3 | 3.18 (1.02) | 0.838–0.864 | 0.807 | 0.886 | 0.722 |
| Behavioural intention (BI) | 3 | 3.15 (1.03) | 0.841–0.868 | 0.818 | 0.892 | 0.734 |
| Sustainable biomedical waste practice (PR) | 4 | 3.18 (0.98) | 0.762–0.857 | 0.841 | 0.893 | 0.678 |

*α, Cronbach's alpha; CR, composite reliability (rho_c); AVE, average variance extracted. Construct scores were measured on a 1–5 scale.*

# Structural model

The structural model explained 41.4% of the variance in behavioural intention ($R^2 = 0.414$; adjusted $R^2 = 0.405$; 95% CI 0.356–0.492) and 46.8% of the variance in sustainable biomedical waste practice ($R^2 = 0.468$; adjusted $R^2 = 0.463$; 95% CI 0.403–0.543). All six antecedent constructs were significantly associated with behavioural intention. Perceived behavioural control showed the strongest association with intention ($\beta = 0.277$, $p < 0.001$, $f^2 = 0.121$), followed by training and organisational support ($\beta = 0.227$, $p < 0.001$), regulatory awareness ($\beta = 0.219$, $p < 0.001$), knowledge ($\beta = 0.204$, $p < 0.001$), and attitude ($\beta = 0.159$, $p < 0.001$). Subjective norms were also significant, although the effect size was small ($\beta = 0.087$, $p = 0.021$, $f^2 = 0.012$). Behavioural intention was the strongest predictor of sustainable biomedical waste practice ($\beta = 0.465$, $p < 0.001$, $f^2 = 0.274$). Perceived behavioural control ($\beta = 0.247$, $p < 0.001$) and training and organisational support ($\beta = 0.118$, $p = 0.005$) also had significant direct effects. Regulatory awareness did not have a significant direct effect ($\beta = 0.062$, $p = 0.110$).

Table 3
Structural model: direct effects

| Path | β | t | p | 95% CI | f² |
|---|---|---|---|---|---|
| KN → BI | 0.204 | 5.45 | < 0.001 | 0.132, 0.278 | 0.065 |
| AT → BI | 0.159 | 4.17 | < 0.001 | 0.085, 0.234 | 0.040 |
| SN → BI | 0.087 | 2.32 | 0.021 | 0.016, 0.164 | 0.012 |
| PC → BI | 0.277 | 7.14 | < 0.001 | 0.199, 0.351 | 0.121 |
| OS → BI | 0.227 | 6.07 | < 0.001 | 0.154, 0.300 | 0.083 |
| RA → BI | 0.219 | 5.84 | < 0.001 | 0.146, 0.291 | 0.074 |
| BI → PR | 0.465 | 11.42 | < 0.001 | 0.385, 0.544 | 0.274 |
| PC → PR | 0.247 | 6.65 | < 0.001 | 0.174, 0.319 | 0.095 |
| OS → PR | 0.118 | 2.83 | 0.005 | 0.038, 0.202 | 0.023 |
| RA → PR | 0.062 | 1.60 | 0.110 | −0.014, 0.137 | 0.006 |

*Bootstrapping used 5,000 subsamples, percentile confidence intervals, and two-tailed significance testing. $R^2$ = 0.414 for BI and 0.468 for PR.*

# Indirect effects through behavioural intention

Behavioural intention transmitted significant indirect effects from all six antecedent constructs to sustainable biomedical waste practice. Knowledge showed a significant indirect effect through behavioural intention (β = 0.095, 95% CI 0.058–0.136), as did attitude (β = 0.074, 95% CI 0.038–0.113) and subjective norms (β = 0.041, 95% CI 0.008–0.079). Because direct paths from knowledge, attitude, and subjective norms to sustainable practice were not specified in the structural model, these are interpreted as significant indirect pathways rather than formally classified mediation types. Perceived behavioural control showed both a significant indirect effect (β = 0.129, 95% CI 0.088–0.172) and a significant direct effect (β = 0.247), producing a total effect of 0.376. Training and organisational support showed a significant indirect effect (β = 0.105, 95% CI 0.069–0.144) and direct effect (β = 0.118), yielding a total effect of 0.223. Regulatory awareness showed a significant indirect effect (β = 0.102, 95% CI 0.066–0.141), while its direct effect was not significant.

Table 4
Indirect, direct and total effects on sustainable biomedical waste practice

| Predictor | Indirect effect (95% CI) | Direct effect | Total effect (95% CI) | Interpretation |
|---|---|---|---|---|
| KN | 0.095 (0.058, 0.136) | Not specified | 0.095 (0.058, 0.136) | Significant indirect pathway through BI |
| AT | 0.074 (0.038, 0.113) | Not specified | 0.074 (0.038, 0.113) | Significant indirect pathway through BI |
| SN | 0.041 (0.008, 0.079) | Not specified | 0.041 (0.008, 0.079) | Significant indirect pathway through BI |
| PC | 0.129 (0.088, 0.172) | 0.247 | 0.376 (0.307, 0.444) | Complementary partial mediation |
| OS | 0.105 (0.069, 0.144) | 0.118 | 0.223 (0.142, 0.305) | Complementary partial mediation |
| RA | 0.102 (0.066, 0.141) | 0.062 (n.s.) | 0.164 (0.085, 0.243) | Indirect effect predominates |

*n.s., not significant; BI, behavioural intention.*

# Predictive performance

PLSpredict produced positive $Q^2$_predict values for all seven endogenous indicators, ranging from 0.205 to 0.297. The PLS-SEM model also produced lower RMSE values than the linear-model benchmark for each endogenous indicator, indicating meaningful out-of-sample predictive performance.

# Differences across facility types

MICOM supported compositional invariance for the public–private and private–specialised comparisons. For the public–specialised comparison, compositional invariance was supported for all constructs except training and organisational support, which narrowly missed the criterion (c = 0.986 compared with a 5% quantile of 0.986). Equality of composite means and variances was not fully supported for subjective norms in two pairwise comparisons. Accordingly, multigroup findings were interpreted on the basis of partial invariance, with additional caution for comparisons involving training and organisational support between public and specialised facilities. Permutation-based multigroup analysis found no statistically significant difference in any structural path across facility types at the 0.05 level. The closest comparisons were knowledge → behavioural intention between private and specialised facilities ($\Delta = -0.205$, $p = 0.053$) and subjective norms → behavioural intention between public and specialised facilities ($\Delta = 0.191$, $p = 0.070$).

Table 5
Path coefficients by facility type and smallest pairwise p-value

| Path | Public (n = 195) | Private (n = 148) | Specialised (n = 77) | Smallest p |
|---|---|---|---|---|
| KN → BI | 0.209 | 0.265 | 0.060 | 0.053 |
| AT → BI | 0.216 | 0.107 | 0.179 | 0.222 |
| SN → BI | 0.047 | 0.106 | 0.238 | 0.070 |
| PC → BI | 0.269 | 0.232 | 0.362 | 0.250 |
| OS → BI | 0.252 | 0.246 | 0.130 | 0.228 |
| RA → BI | 0.256 | 0.159 | 0.255 | 0.251 |
| BI → PR | 0.401 | 0.538 | 0.405 | 0.120 |
| PC → PR | 0.329 | 0.216 | 0.171 | 0.146 |
| OS → PR | 0.184 | 0.075 | 0.054 | 0.244 |
| RA → PR | 0.100 | −0.004 | 0.184 | 0.121 |

*Permutation test based on 1,000 permutations, two-tailed, with three pairwise comparisons per structural path.*

Knowledge (KN), attitude (AT), subjective norms (SN), perceived behavioural control (PC), training and organisational support (OS), and regulatory awareness (RA) predict behavioural intention (BI). BI, PC, OS, and RA predict sustainable biomedical waste-management practice (PR). Values on structural paths are standardised coefficients (β); outer loadings are reported in Table 2. BI explained 41.4% of its variance ($R^2 = 0.414$), while the model explained 46.8% of the variance in PR ($R^2 = 0.468$). BI was the strongest predictor of PR ($\beta = 0.465$, $p < 0.001$), followed by PC ($\beta = 0.247$, $p < 0.001$) and OS ($\beta = 0.118$, $p = 0.005$). The RA → PR path was not significant ($\beta = 0.062$, $p = 0.110$).

# Discussion

This study examined the drivers of sustainable biomedical waste-management practices among healthcare workers in Dhaka using an extended TPB framework. The model explained 41.4% of the variance in behavioural intention and 46.8% of the variance in sustainable practice. Behavioural intention emerged as the strongest predictor of practice, while perceived behavioural control and training and organisational support also retained significant direct effects. All six antecedent constructs were significantly associated with behavioural intention, although their contributions differed. Regulatory awareness influenced practice primarily through behavioural intention, and no statistically significant differences in structural paths were identified across facility types.

The strong association between behavioural intention and sustainable practice is consistent with the central proposition of TPB, in which intention represents the most proximal motivational determinant of behaviour [21–28]. In the present study, behavioural intention had the largest direct effect on practice (β = 0.465). This suggests that healthcare workers who were more willing and prepared to follow sustainable biomedical waste-management procedures were also more likely to report performing them. Similar intention–behaviour relationships have been documented across health, environmental, recycling, and occupational behaviours [23–28].

The explanatory importance of behavioural intention also supports the use of a behavioural framework rather than relying solely on knowledge-attitude-practice approaches. KAP studies can identify whether healthcare workers know appropriate procedures or hold favourable attitudes, but they do not necessarily explain how these factors are translated into action. The present findings show that knowledge, attitude, subjective norms, perceived behavioural control, organisational support, and regulatory awareness were all associated with intention, which in turn was strongly related to practice. This pattern suggests that intention may be an important mechanism through which several individual and contextual influences are translated into routine biomedical waste-management behaviour [19,20,36].

Among the antecedents of behavioural intention, perceived behavioural control showed the strongest association. It also retained a substantial direct effect on sustainable practice and had the largest total effect among the predictors examined. This is theoretically important because perceived behavioural control captures whether individuals believe that they have the capacity, opportunity, and practical ability to perform a behaviour [21–25]. In biomedical waste management, workers may understand recommended procedures and be motivated to follow them, but compliance can still depend on whether segregation containers, protective equipment, disposal systems, time, and institutional support are available [2,8–12,29–33]. The direct and indirect effects observed here therefore suggest that perceived control operates both by strengthening motivation and by facilitating translation of intention into practice.

Training and organisational support also had an important role. The construct was significantly associated with behavioural intention and had a smaller but significant direct effect on practice. Its indirect effect through intention was also significant, indicating complementary partial mediation. Supportive organisational environments may influence behaviour by strengthening workers' willingness to follow procedures and by providing the resources, supervision, routines, and reinforcement required to perform them [29–33]. This finding reinforces the view that healthcare waste management is an organisational systems issue as well as an individual behavioural issue.

Regulatory awareness showed a different pattern. It significantly predicted behavioural intention but did not have a statistically significant direct association with practice. The indirect effect through intention was nevertheless significant. Awareness of regulations may therefore influence behaviour primarily by shaping motivation, perceived responsibility, and compliance intentions rather than by directly producing

action [13,34,35]. Knowledge of rules alone may be insufficient if organisational systems, infrastructure, and practical control are weak.

Knowledge was positively associated with behavioural intention and showed a significant indirect pathway to practice through intention. This reinforces the importance of knowledge but also indicates that knowledge should not be interpreted as an independent guarantee of sustainable practice. Healthcare workers may know how biomedical waste should be segregated or disposed of but may still fail to act consistently if they perceive limited control, weak organisational support, or inadequate institutional reinforcement [19,20].

Attitude was also significantly associated with behavioural intention, although its effect was smaller than those of perceived behavioural control, organisational support, regulatory awareness, and knowledge. This suggests that favourable evaluations of sustainable waste-management practices contribute to intention but may be less influential than practical control or institutional support. Subjective norms showed the weakest significant effect. In highly structured work environments such as hospitals and diagnostic facilities, behaviour may be shaped more strongly by formal systems and practical constraints than by interpersonal expectations alone [21–28].

The mediation findings clarify how the antecedent constructs relate to sustainable practice. Perceived behavioural control and training and organisational support showed significant direct and indirect effects, suggesting that both motivation and enabling conditions matter. Regulatory awareness operated primarily through behavioural intention. Knowledge, attitude, and subjective norms also showed significant indirect pathways through intention, although direct paths from these constructs to practice were not specified. These findings should therefore be interpreted as evidence of indirect pathways rather than definitive indirect-only mediation [37,45].

The model also demonstrated meaningful predictive performance. Positive $Q^2$_predict values were obtained for all endogenous indicators, and the PLS model produced lower RMSE values than the linear-model benchmark for each indicator. This indicates that the model was not only explanatory but also showed useful out-of-sample predictive capability [39,49].

No statistically significant differences in structural paths were identified across public, private, and specialised or diagnostic facilities. This suggests that the broad pattern of relationships may be relatively stable across facility types. However, the specialised or diagnostic group was smaller, and compositional invariance was not fully established for training and organisational support in the public–specialised comparison. The absence of significant multigroup differences should therefore not be interpreted as proof that all facility types operate identically [48].

The findings have practical implications. Interventions should not focus exclusively on increasing knowledge. Educational programmes remain important, but their impact may be limited if healthcare workers do not feel capable of performing required behaviours or if organisational conditions do not support them. Healthcare facilities should therefore strengthen practical control by ensuring access to

segregation materials, protective equipment, clear disposal procedures, and adequate infrastructure. Training should be embedded within wider organisational support systems that include supervision, feedback, role clarity, and accountability. Regulatory communication should likewise be linked to implementation rather than relying on awareness alone [2,8–13,29–35].

# Strengths and limitations

This study included healthcare workers from public, private, and specialised or diagnostic facilities and incorporated multiple occupational groups involved in biomedical waste handling. The analytical framework extended TPB by incorporating organisational and regulatory factors and examined both direct and indirect pathways. The analysis also included out-of-sample prediction and multigroup comparison. Several limitations should be considered. The cross-sectional design prevents causal inference. All measures were self-reported and may be affected by recall or social-desirability bias. Although full-collinearity VIFs did not indicate problematic common-method bias under the applied criterion, such bias cannot be ruled out completely [47]. Healthcare facilities were selected on the basis of availability and willingness to participate, and eligible workers were approached within participating facilities rather than sampled from a complete probability-based frame, limiting generalisability beyond participating facilities in Dhaka. A formal response rate could not be calculated. The specialised or diagnostic subgroup was relatively small, reducing power for multigroup comparisons. Finally, sustainable biomedical waste practice was assessed through self-report rather than direct observation.

# Implications for future research

Future studies should test the model longitudinally to determine whether changes in behavioural intention precede changes in sustainable biomedical waste-management practice. Intervention studies could examine whether improvements in perceived behavioural control, organisational support, or regulatory implementation lead to measurable behavioural change. Direct observation of segregation and disposal practices would complement self-reported measures. Future models could also incorporate leadership commitment, infrastructure availability, workload, institutional culture, perceived enforcement, environmental concern, and occupational safety climate.

## Conclusion

Sustainable biomedical waste-management practice among healthcare workers was shaped by a combination of behavioural, organisational, and regulatory factors. Behavioural intention was the strongest predictor of sustainable practice, while perceived behavioural control and training and organisational support also showed significant direct associations. Perceived behavioural control had the largest total effect on practice, suggesting that healthcare workers are more likely to follow sustainable procedures when they perceive that appropriate behaviours are feasible and within their control. Knowledge, attitude, subjective norms, perceived behavioural control, training and organisational support, and regulatory awareness were all positively associated with behavioural intention. Regulatory

awareness was not directly associated with sustainable practice but showed a significant indirect effect through intention. These findings suggest that improving biomedical waste management requires more than knowledge-based training alone. Healthcare facilities should combine education with adequate infrastructure, access to protective and segregation materials, supportive supervision, clear procedures, and practical implementation of regulatory requirements.

## Abbreviations

AT
Attitude
AVE
Average variance extracted
BI
Behavioural intention
CI
Confidence interval
CR
Composite reliability
HTMT
Heterotrait-monotrait ratio
KAP
Knowledge, attitude and practice
KN
Knowledge
MICOM
Measurement invariance of composites
OS
Training and organisational support
PC
Perceived behavioural control
PLS-SEM
Partial least squares structural equation modelling
PR
Sustainable biomedical waste-management practice
RA
Regulatory awareness
RMSE
Root mean square error
SD
Standard deviation

SN
Subjective norms
STROBE
Strengthening the Reporting of Observational Studies in Epidemiology
TPB
Theory of planned behaviour
VIF
Variance inflation factor

## Declarations

# Ethics approval and consent to participate

The study was approved by the Ethical Review Committee of Manabik Shahajya Sangstha (MSS) (reference no. MSS-ERC-SFP-R-43/2026; approval date 15 February 2026). All participants were informed about the purpose of the study before participation. Participation was voluntary, and informed consent was obtained from all participants before completion of the questionnaire.

# Consent for publication

Not applicable.

# Availability of data and materials

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

# Competing interests

The authors declare that they have no competing interests.

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# Authors' contributions

Shabbir Abdullah Maruf conceptualized the study. Md. Rajiur Rahman Arif, Most Sakila Azmin and Md Tanvir Mahatab contributed to study design and methodology. Iqbal Hossain andFarhana Zaman, coordinated data collection. Raihana Jaman keya performed and supervised the statistical analysis. Shabbir Abdullah Maruf interpreted the findings. Shahana Mannan prepared the initial manuscript draft. All authors critically reviewed and revised the manuscript, approved the final version, and agreed to be accountable for the work.


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# Use of artificial intelligence tools

Generative artificial intelligence tools were used to support language editing . The statistical model and analyses were conducted independently using SmartPLS. All authors reviewed the AI-assisted text, verified the scientific content and interpretation of the results, and take full responsibility for the final manuscript.

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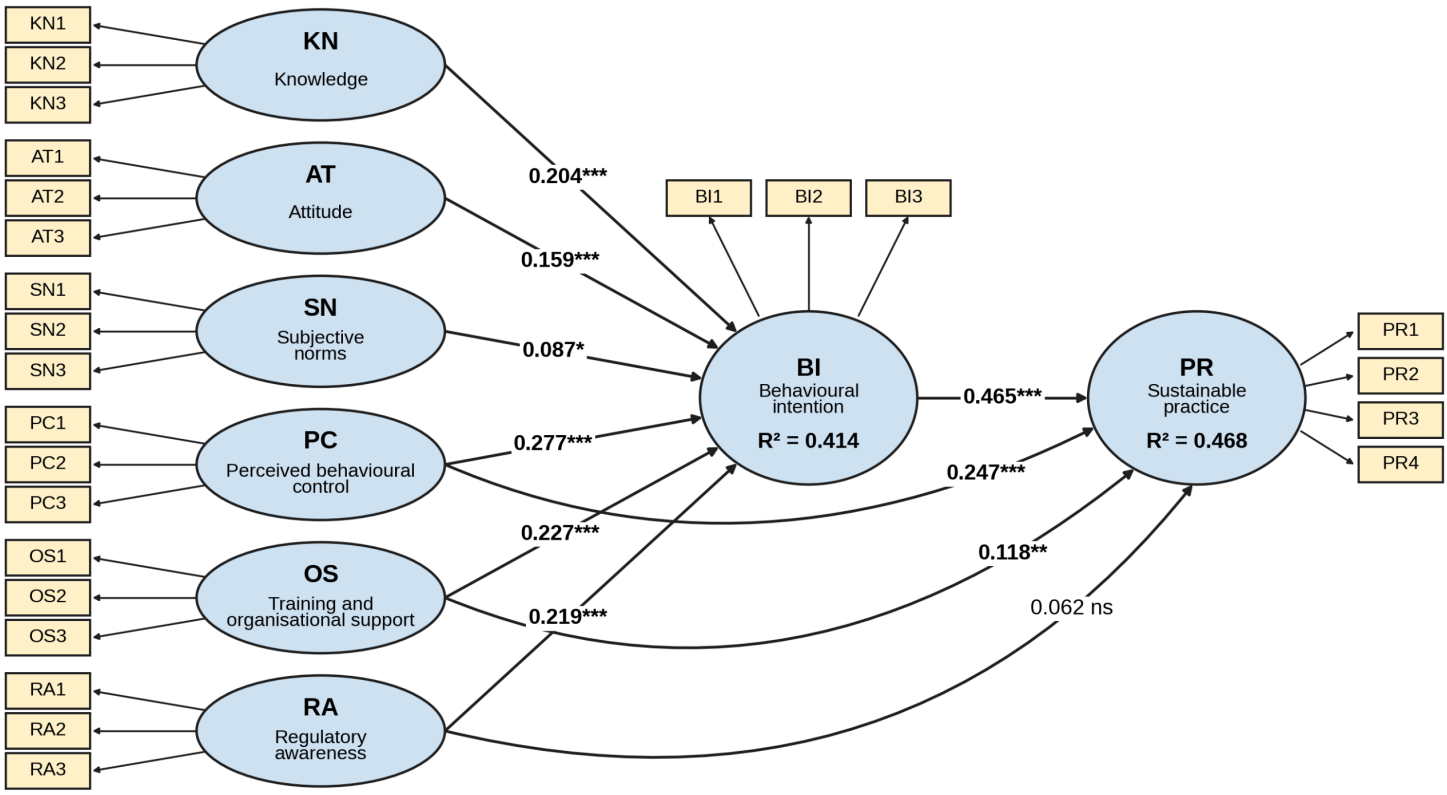

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# Figures




*** p < 0.001; ** p < 0.01; * p < 0.05; ns = not significant. Path values are standardised coefficients (β).

**Figure 1**

**Structural model with standardised path coefficients, significance levels and R² values.**

Knowledge (KN), attitude (AT), subjective norms (SN), perceived behavioural control (PC), training and organisational support (OS), and regulatory awareness (RA) predict behavioural intention (BI). BI, PC, OS, and RA predict sustainable biomedical waste-management practice (PR). Values on structural paths are standardised coefficients (β); outer loadings are reported in Table 2. BI explained 41.4% of its variance ($R^2 = 0.414$), while the model explained 46.8% of the variance in PR ($R^2 = 0.468$). BI was the strongest predictor of PR ($\beta = 0.465$, $p < 0.001$), followed by PC ($\beta = 0.247$, $p < 0.001$) and OS ($\beta = 0.118$, $p = 0.005$). The RA → PR path was not significant ($\beta = 0.062$, $p = 0.110$).