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Factors associated with sustainable biomedical waste management practices among healthcare workers in Bangladesh: a cross-sectional structural equation modelling study

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Abstract

Sustainable biomedical waste management protects healthcare workers, patients, communities and the environment. This cross-sectional, facility-based survey examined factors associated with sustainable biomedical waste-management practice among 420 healthcare workers from 5 public hospitals, 10 private hospitals and 13 specialised or diagnostic facilities in Dhaka, Bangladesh, between May and September 2026. Using an extended theory of planned behaviour framework, partial least squares structural equation modelling (SmartPLS 4.1.2.1) estimated associations among six antecedent constructs, behavioural intention and self-reported practice. The model explained 41% of the variance in intention and 47% in practice. All six antecedents were positively associated with intention; perceived behavioural control showed the strongest association ($\beta = 0.28$, $p < 0.001$), followed by training and organisational support ($\beta = 0.23$), regulatory awareness ($\beta = 0.22$), knowledge ($\beta = 0.20$), attitude ($\beta = 0.16$) and subjective norms ($\beta = 0.09$, $p = 0.02$). Behavioural intention was most strongly associated with practice ($\beta = 0.47$, $p < 0.001$), followed by perceived behavioural control ($\beta = 0.25$, $p < 0.001$) and training and organisational support ($\beta = 0.12$, $p < 0.01$). Regulatory awareness showed no significant direct association with practice ($\beta = 0.06$, $p = 0.11$). Out-of-sample predictive performance was meaningful, and no significant structural-path differences were detected across facility types. Because the design is cross-sectional, the findings indicate associations rather than causal or mediating effects. Interventions should combine knowledge-based training with supportive organisational systems, adequate resources and effective implementation of regulatory requirements.

Introduction

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 see how knowledge, organisational support, and regulatory awareness are associated with intention and with practice when examined together. A multivariable structural model can describe these associations simultaneously, 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 factors related to sustainable biomedical waste management among healthcare workers in Bangladesh remains limited. The present study therefore examined factors associated with 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 correlates of behavioural intention. Behavioural intention, perceived behavioural control, training and organisational support, and regulatory awareness were then examined as correlates of sustainable practice. Because the data are cross-sectional, the study describes associations and does not test causal or mediating processes. It further assessed 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 factors associated with 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, interrelated associations, 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. The model was theory-guided, and its paths represent statistical associations estimated from cross-sectional data rather than causal effects.

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]. Exploratory indirect and total associations through behavioural intention were calculated with bootstrapped confidence intervals and are reported in Online Resource 1. Because the data are cross-sectional, these estimates are not interpreted as evidence of causal mediation.

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 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 (Table 1). 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 (Table 2). All indicator loadings exceeded 0.70, ranging from 0.76 to 0.89. Cronbach's alpha values ranged from 0.79 to 0.84, composite reliability values from 0.88 to 0.90, and AVE from 0.68 to 0.75. The highest HTMT value was 0.76 for behavioural intention and sustainable biomedical waste practice, and the corresponding bootstrapped 95% upper confidence bound was 0.81. 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)	0.86–0.87	0.84	0.90	0.75
Attitude (AT)	3	3.16 (1.05)	0.85–0.86	0.81	0.89	0.73
Subjective norms (SN)	3	3.14 (1.02)	0.79–0.89	0.80	0.88	0.71
Perceived behavioural control (PC)	3	3.04 (1.01)	0.83–0.84	0.79	0.88	0.70
Training and organisational support (OS)	3	3.12 (1.02)	0.83–0.85	0.79	0.88	0.71
Regulatory awareness (RA)	3	3.18 (1.02)	0.84–0.86	0.81	0.89	0.72
Behavioural intention (BI)	3	3.15 (1.03)	0.84–0.87	0.82	0.89	0.73
Sustainable biomedical waste practice (PR)	4	3.18 (0.98)	0.76–0.86	0.84	0.89	0.68

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% of the variance in behavioural intention ($R^2 = 0.41$; adjusted $R^2 = 0.41$; 95% CI 0.36–0.49) and 47% of the variance in sustainable biomedical waste practice ($R^2 = 0.47$; adjusted $R^2 = 0.46$; 95% CI 0.40–0.54). All six antecedent constructs were significantly associated with behavioural intention (Table 3, Fig. 1). Perceived behavioural control showed the strongest association with intention ($\beta = 0.28$, $p < 0.001$, $f^2 = 0.12$), followed by training and organisational support ($\beta = 0.23$, $p < 0.001$), regulatory awareness ($\beta = 0.22$, $p < 0.001$), knowledge ($\beta = 0.20$, $p < 0.001$), and attitude ($\beta = 0.16$, $p < 0.001$). Subjective norms were also significant, although the effect size was small ($\beta = 0.09$, $p = 0.02$, $f^2 = 0.01$). Behavioural intention was most strongly associated with sustainable biomedical waste practice ($\beta = 0.47$, $p < 0.001$, $f^2 = 0.27$). Perceived behavioural control ($\beta = 0.25$, $p < 0.001$) and training and organisational support ($\beta = 0.12$, $p < 0.01$) were also significantly associated with practice. Regulatory awareness was not significantly associated with practice ($\beta = 0.06$, $p = 0.11$).

Table 3
Structural model: standardised path coefficients

Path	β	t	p	95% CI	f^2
KN → BI	0.20	5.45	< 0.001	0.13, 0.28	0.07
AT → BI	0.16	4.17	< 0.001	0.09, 0.23	0.04
SN → BI	0.09	2.32	0.02	0.02, 0.16	0.01
PC → BI	0.28	7.14	< 0.001	0.20, 0.35	0.12
OS → BI	0.23	6.07	< 0.001	0.15, 0.30	0.08
RA → BI	0.22	5.84	< 0.001	0.15, 0.29	0.07
BI → PR	0.47	11.42	< 0.001	0.39, 0.54	0.27
PC → PR	0.25	6.65	< 0.001	0.17, 0.32	0.10
OS → PR	0.12	2.83	< 0.01	0.04, 0.20	0.02
RA → PR	0.06	1.60	0.11	−0.01, 0.14	0.01

Bootstrapping used 5,000 subsamples, percentile confidence intervals, and two-tailed significance testing. R^2 = 0.41 for BI and 0.47 for PR.

Standardised path coefficients (β) are shown on the paths: knowledge (KN), attitude (AT), subjective norms (SN), perceived behavioural control (PC), training and organisational support (OS), and regulatory awareness (RA) with behavioural intention (BI), and BI, PC, OS, and RA with sustainable biomedical waste-management practice (PR). *** p < 0.001, ** p < 0.01, * p < 0.05, ns not significant. Indicators and outer loadings are reported in Table 2. BI explained 41% of its variance (R^2 = 0.41), and the model explained 47% of the variance in PR (R^2 = 0.47)

Exploratory indirect associations

Exploratory indirect and total associations through behavioural intention are reported in Online Resource 1 (Table S1). The indirect associations were statistically significant for all six antecedent constructs, but because intention and practice were measured at the same time, these estimates are not interpreted as mediation.

Predictive performance

PLSpredict produced positive Q^2_predict values for all seven endogenous indicators, ranging from 0.21 to 0.30. 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 (Table 4). The closest comparisons were knowledge → behavioural intention between private and specialised facilities (Δ = −0.21, p = 0.053) and subjective norms → behavioural intention between public and specialised facilities (Δ = 0.19, p = 0.07).

Table 4
Path coefficients by facility type and smallest pairwise p-value

Path	Public (n = 195)	Private (n = 148)	Specialised (n = 77)	Smallest p
KN → BI	0.21	0.27	0.06	0.053
AT → BI	0.22	0.11	0.18	0.22
SN → BI	0.05	0.11	0.24	0.07
PC → BI	0.27	0.23	0.36	0.25
OS → BI	0.25	0.25	0.13	0.23
RA → BI	0.26	0.16	0.26	0.25
BI → PR	0.40	0.54	0.41	0.12
PC → PR	0.33	0.22	0.17	0.15
OS → PR	0.18	0.08	0.05	0.24
RA → PR	0.10	0.00	0.18	0.12

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

Discussion

This study examined factors associated with sustainable biomedical waste-management practices among healthcare workers in Dhaka using an extended TPB framework. The model explained 41% of the variance in behavioural intention and 47% of the variance in sustainable practice. Behavioural intention was most strongly associated with practice, while perceived behavioural control and training and organisational support were also significantly associated with practice. All six antecedent constructs were significantly associated with behavioural intention, although their contributions differed. Regulatory

awareness was associated with intention but not directly with practice, 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 strongest association with practice ($\beta = 0.47$). 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 is consistent with the theoretical proposition that intention links several individual and contextual factors to routine biomedical waste-management behaviour, although cross-sectional data cannot establish this sequence [19, 20, 36].

Among the antecedents of behavioural intention, perceived behavioural control showed the strongest association. It was also directly associated with sustainable practice. 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 associations observed here are therefore consistent with perceived control relating both to motivation and to the practical ability to perform the behaviour, although the design cannot distinguish between these routes.

Training and organisational support also had an important role. The construct was significantly associated with behavioural intention and was also directly associated with practice, although more weakly. Supportive organisational environments may be related to 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 was significantly associated with behavioural intention but not directly with practice. Awareness of regulations may therefore be related to behaviour mainly through motivation, perceived responsibility, and compliance intentions rather than direct action,

although longitudinal data would be needed to test this [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. 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 association. 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].

Exploratory indirect associations through behavioural intention (Online Resource 1) were consistent with the structure of the TPB-based model. Because all constructs were measured simultaneously by self-report, however, the temporal ordering needed to establish mediation is absent, and these estimates should be read as descriptive associations rather than evidence of mediating mechanisms [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].

Although causal conclusions cannot be drawn, 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 the associations among these constructs simultaneously. The analysis also included out-of-sample prediction and multigroup comparison. Several limitations should be considered. The cross-sectional design prevents causal inference, and cross-sectional estimates of indirect (mediating) relationships can be biased because the temporal ordering of intention and practice cannot be established [50, 51]. 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 associated with a combination of behavioural, organisational, and regulatory factors. Behavioural intention was most strongly associated with sustainable practice, while perceived behavioural control and training and organisational support were also directly associated with practice. Perceived behavioural control showed the strongest association with intention, suggesting that healthcare workers may be more likely to intend 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 associated with intention but not directly with practice. 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. Longitudinal studies are needed to test the sequence implied by these associations.

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.

Competing interests

The authors declare that they have no competing interests.

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Author Contribution

Shabbir Abdullah Maruf conceptualized the study. Md. Rajiur Rahman Arif, Most Sakila Azmin, and Md Tanvir Mahatab contributed to the study design and methodology. Iqbal Hossain and Farhana 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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Data Availability

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

Use of artificial intelligence tools

Generative artificial intelligence tools were used to support language editing of the manuscript. 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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Figures

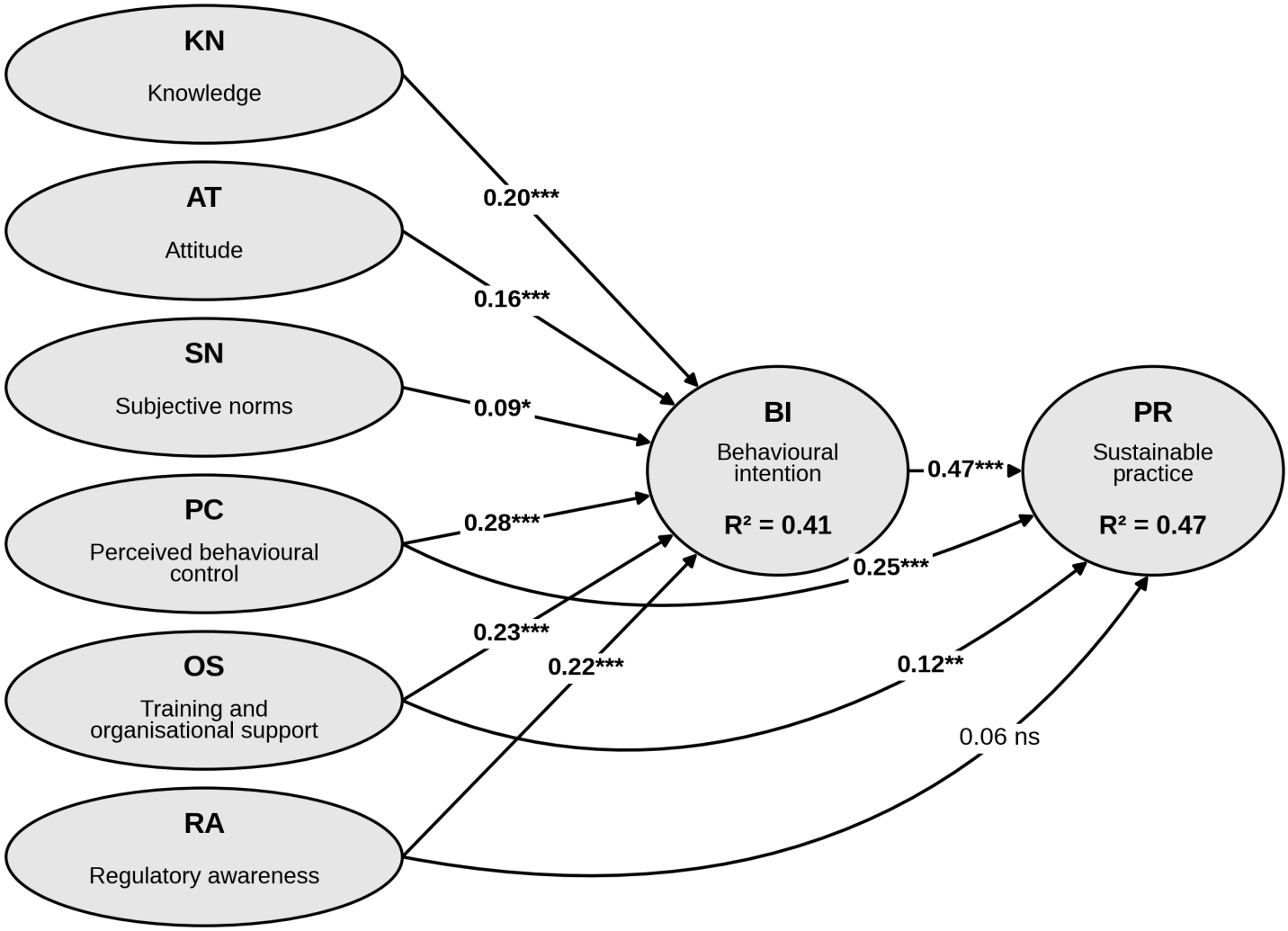


Figure 1

Structural model of associations among the study constructs

Standardised path coefficients (β) are shown on the paths: knowledge (KN), attitude (AT), subjective norms (SN), perceived behavioural control (PC), training and organisational support (OS), and regulatory awareness (RA) with behavioural intention (BI), and BI, PC, OS, and RA with sustainable biomedical waste-management practice (PR). *** p < 0.001, ** p < 0.01, * p < 0.05, ns not significant. Indicators and outer loadings are reported in Table 2. BI explained 41% of its variance ($R^2 = 0.41$), and the model explained 47% of the variance in PR ($R^2 = 0.47$)

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