Pisco Med Publishing

Human Resources Management and Services 2026, 8(4), 6624.
https://doi.org/10.18282/hrms6624

Article

Tech-savvy leadership, HR practices, and workforce mental health in Bangladesh's IT industry

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CITATION

Prince SA, Rahman MM, Wahid IS. (2026). Tech-savvy leadership, HR practices, and workforce mental health in Bangladesh's IT industry. Human Resources Management and Services. 8(4): 6624. https://doi.org/10.18282/hrms6624

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Abstract: Grounded in Job Demands–Resources (JD–R) theory and Work–Family Enrichment theory, this study investigates how tech-savvy leadership and behavioral clarity relate to workforce engagement and, in turn, to workforce mental health in Bangladesh's rapidly expanding IT industry. It also examines the associations of work–life balance and peer support with workforce mental health and the mediating role of work–life balance in the relationship between workforce engagement and workforce mental health. Survey data were collected from 419 professionals employed in local and multinational IT firms and analyzed using SPSS and SmartPLS 4. The Partial Least Squares Structural Equation Modeling results show that tech-savvy leadership and behavioral clarity are positively associated with workforce engagement, which in turn is positively associated with work–life balance and workforce mental health. Work–life balance is also directly and positively associated with mental health, and social support from peers is positively associated with workforce mental health, although the association is modest. However, work–life balance did not significantly mediate the relationship between workforce engagement and mental health under the pre-specified t-test criterion, although the percentile bootstrap confidence interval narrowly excluded zero. These findings contribute to bridging the identified research gaps and offer implications for researchers, policymakers, Human Resource practitioners, and Information Technology leaders by highlighting the importance of engagement-focused management, peer support, and balanced work arrangements in promoting workforce mental health in Bangladesh's digital economy.

Keywords: tech-savvy leadership, behavioral clarity, workforce engagement, workforce mental health

1. Introduction

Mental health has become a key component of workforce sustainability in the knowledge economy, particularly in technologically intensive sectors, such as information technology (IT) (Liswandi & Muhammad, 2023). The faster digital transformation of businesses has reformed leadership styles and organizational practices, highlighting the importance of supportive leadership and workplace environments in ensuring employee well-being. Leaders are increasingly expected to drive performance and foster psychological resilience among their teams (Zhu et al., 2022).

Bangladesh is a developing nation whose IT sector is growing rapidly and contributing significantly to employment and Gross Domestic Product. However, the expansion of IT has also introduced new pressures on employees, including work overload, role ambiguity, and digital fatigue—factors that have been linked

to poorer mental health (Khan et al., 2026). Despite the global discourse on workplace mental health, empirical studies examining how leadership and organizational clarity relate to psychological well-being in emerging economies remain limited.

Tech-savvy leadership, defined in this study as an immediate supervisor's technology-related competence and enabling behavior toward subordinates, is related to the broader constructs of digital leadership and e-leadership, which have been linked to employee work engagement and leadership in technology-mediated settings (Li et al., 2024; Avolio & Kahai, 2003). However, the concept remains under-theorized in contrast to broader digital leadership constructs (Hooi & Chan, 2023). Behavioral clarity, another key organizational attribute, reduces ambiguity and promotes employee confidence, thereby enhancing work engagement (Majid et al., 2023). However, most research on these relationships has been conducted in developed economies or in neighboring economies such as India and Pakistan, leaving a significant gap in the context of Bangladesh.

Moreover, the relationships among leadership, engagement, work–life balance, and mental health require further study, particularly through mediated frameworks. For example, supervisory appreciation—employees' perceptions of being valued by their supervisors—has been shown to strengthen the positive effects of leadership on engagement and well-being (Panda et al., 2022). Furthermore, work–life balance and peer support have also been recognized as important mediators and moderators of employee well-being (Zhang et al., 2024; Myrick & Del Vecchio, 2016). However, the interconnected nature of these variables has rarely been researched in an integrated framework.

This study seeks to address these knowledge gaps by examining how tech-savvy leadership and behavioral clarity are associated with workforce engagement, and how workforce engagement, work–life balance, and social support from peers are associated with workforce mental health, including the mediating role of work–life balance between engagement and mental health. The present study is framed on the basis of Job Demands–Resources Theory (Demerouti et al. (2001) and investigates how workplace positive measures can contribute to the generation of emotional resources that are useful for the permanent well-being of employees in the IT sector of Bangladesh.

Despite growing recognition of the importance of mental health in the workplace, empirical evidence from emerging economies, particularly Bangladesh, remains scarce. Most prior studies have focused on developed countries or regional neighbors such as India and Pakistan, leaving a contextual gap in understanding how tech-savvy leadership and behavioral clarity function in a rapidly digitizing workforce. Moreover, most existing research has examined direct relationships between leadership and engagement or mental health, without integrating mediating mechanisms such as work–life balance or accounting for social support from peers. This fragmented approach limits insights into the combined and conditional effects of these factors on employees' psychological well-being. Therefore, this study addresses these gaps by investigating how tech-savvy leadership and behavioral clarity relate to workforce engagement, how engagement relates to work–life balance and mental health outcomes, and how peer support relates directly to mental well-being. The objectives are threefold: (1) to examine the associations of tech-savvy leadership and behavioral clarity with workforce engagement; (2) to examine the associations of workforce engagement with work–life balance, and of workforce engagement, work–life balance, and social support from peers with workforce mental health; and (3) to examine whether work–life balance mediates the association between workforce engagement and workforce mental health.

In terms of contribution, this study provides both theoretical and practical

insights that advance scholarship and inform policy in the IT sector. Theoretically, it examines tech-savvy leadership, a supervisor-level, competence-based construct that is related to, but narrower than, digital leadership and e-leadership, and examines the motivational pathway of the Job Demands–resources model in a professional, high-tech environment, extending its application to an emerging economy. Drawing on work–family enrichment theory, it also links workforce engagement to employees' work–life balance, thereby connecting workplace resources to employees' lives outside work. From a policy and managerial perspective, the findings offer guidance for HR professionals, IT leaders, and policymakers in Bangladesh: fostering engagement-focused leadership, enhancing clarity in organizational practices, promoting peer support networks, and supporting work–life balance may be associated with better engagement and mental health among IT professionals. By bridging theoretical insights with practical recommendations, this study contributes to the discourse on sustainable employee well-being in rapidly digitizing labor markets in several ways.

2. Literature review and hypotheses development

2.1. Tech-savvy leadership and workforce engagement

Tech-savvy leadership refers to an immediate supervisor's technology-related competence and enabling behavior toward subordinates. It comprises three facets: (a) technological knowledge, a working understanding of the technologies relevant to the team's work processes; (b) technology application, the identification and use of appropriate technologies to improve work processes and team performance; and (c) technology enablement, guidance that helps employees adopt and effectively use new technologies. The term "tech-savvy" has been used to describe school district leaders who personally model technology use and invest in professional development for technology integration (McLeod et al., 2015); this study extends the concept to employees' immediate supervisors. This study adopts the Job Demands-Resources (JD-R) model as its primary theoretical framework. Within the JD-R model, tech-savvy leadership is a supervisory resource because it can reduce technology-related uncertainty, improve access to useful tools, and build employees' technological confidence. Leaders who use digital platforms effectively, encourage appropriate technology adoption, and provide support for technological learning can help employees work more efficiently and feel more capable in technology-mediated tasks. These conditions are likely to increase engagement because employees perceive that the work environment supports goal achievement and competence development.

There is scarce available evidence on tech-savvy leadership and its relationship with workforce engagement in the IT industry. Although digital leadership has been the focus of some studies, there has been scant research on the direct relationship between tech-savvy leadership and employee engagement. For instance, Li et al. (2024) examined middle managers' digital leadership and found that it was positively related to employee work engagement. Additionally, Hooi and Chan (2023) examined the influence of workplace digitalization and found that leaders who embrace digital innovation are more likely to have engaged employees. Although these studies provide important insights into digital leadership, they do not specifically address technologically adept leadership in the organizational context of the IT industry.

Tech-savvy leadership should be distinguished from two related constructs. Digital leadership concerns the digital transformation of the organization (Kane et al., 2019); El Sawy et al. (2016) describe it as leadership aimed at the strategic success of digitalization for the enterprise and its business ecosystem, which requires new thinking about business strategy, business models, enterprise platforms, and the workplace. E-leadership refers to a

social influence process mediated by advanced information technology that can change the attitudes, feelings, thinking, behavior, and performance of individuals, groups, or organizations (Avolio et al., 2014); its emphasis is on leadership exercised through technology, particularly in virtual or technology-mediated settings (Avolio & Kahai, 2003). By contrast, tech-savvy leadership operates at the supervisor and team levels and concerns the supervisor's own technological competence and the extent to which the supervisor enables subordinates to use technology effectively. A supervisor may therefore be tech-savvy without leading organizational transformation, as in digital leadership, and without leading primarily through technology-mediated channels, as in e-leadership. This distinction is relevant to the present study, in which most respondents (94.5%) worked on-site: in predominantly face-to-face work settings, the supervisor's technological competence and support are likely to be more salient than leadership exercised through electronic channels. **Table 1** shows the three items used to measure tech-savvy leadership and the fact that each item represents.

This distinction points to the need for more empirical research on the distinct relationship between tech-savvy leadership and employee engagement, especially in high-tech sectors such as the IT industry. This gap underscores the importance of exploring how technology-savvy leadership relates to workforce engagement in technology-rich contexts.

Based on the aforementioned discussion, the primary hypothesis tested in our study was as follows:

H1: Tech-savvy leadership is positively associated with workforce engagement.

2.2. Behavioral clarity and workforce engagement

Behavioral clarity refers to employees' perception that managerial instructions, expectations, goals, deadlines, and work boundaries are well-defined. Behavioral clarity is a job resource because it reduces ambiguity and enables employees to direct their attention, energy, and effort toward meaningful tasks. When employees understand what is expected of them, they are more likely to feel confident, purposeful, and psychologically available to perform their work. Prior research has shown that role clarity contributes to job engagement, intrinsic motivation, and innovative work behaviors.

Previous studies have highlighted the importance of role clarity in enhancing workforce engagement and employee outcomes. For instance, Majid et al. (2023) studied role clarity in the Pakistani hospitality sector and found it to be a substantial contributor to job engagement, suggesting that employees' engagement and proactivity depended strongly on whether they knew what was expected of them. Similarly, Kundu et al. (2020) explored the effect of perceived role clarity on innovative work behavior in Indian workplaces. These studies found that role clarity positively influenced intrinsic motivation and job involvement, key components of employee engagement. These studies support the hypothesis that behavioral clarity is positively associated with workforce engagement. However, both studies were conducted in Pakistan and India and did not consider the Bangladeshi context, particularly within the IT sector. This highlights the need for research focused explicitly on the IT sector in Bangladesh.

From the above discussion, establishing a link between role clarity and workforce engagement in other contexts is essential to assess whether this relationship is genuine in the IT sector in Bangladesh. Therefore, this study proposes the following hypothesis:

H2: Behavioral clarity is positively associated with workforce engagement.

2.3. Workforce engagement and workforce mental health

Workforce engagement reflects employees' involved and connected

participation in their work. In the JD-R model, engagement is the central motivational state through which workplace resources are translated into positive outcomes (Schaufeli & Bakker, 2004). Engaged employees are more likely to experience meaning, competence, voice, and organizational connection, all of which support psychological well-being.

In this study, workforce mental health is understood as employees' positive work-related mental health. Following the World Health Organization's (2022) definition of mental health as a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community, which is more than the absence of mental disorder, the construct captures employees' perceived ability to maintain their psychological well-being at work, their sense of purpose and accomplishment in their work, and their perception that their organization values and supports employees' mental health. Therefore, it is a positive, perception-based indicator of mental health at work and not a clinical measure of psychological symptoms or mental disorders.

The relationship between workforce engagement and mental health has garnered significant attention in organizational research. For instance, Khan et al. (2026) examined how employee engagement practices influence mental health in the Indian IT sector. Their study found that engagement practices positively affect employee voice, enhancing mental health. As Khan et al. (2026) affirm the hypothesis that workforce engagement positively affects workforce mental health in India, our study considered the empirical findings and developed the following hypotheses:

H3: Workforce engagement is positively associated with workforce mental health.

2.4. Workforce engagement and work–life balance

The relationship between workforce engagement and work–life balance (WLB) has garnered significant attention in organizational research. Drawing on the motivational pathway of the JD-R model, our study assumes that workforce engagement provides employees with a sense of support, voice, and belonging, and psychological resources that help them manage job demands more effectively. Consequently, engaged employees are better able to balance their work and personal responsibilities, leading to improved work–life balance. Several empirical studies support the view that WLB is positively related to workforce engagement; however, few studies have examined the relationship in the opposite direction, that is, whether workforce engagement is positively related to WLB.

Work–family enrichment theory provides a more specific rationale for this. The sense of support and belonging and positive affect associated with engagement may spill over into the non-work domain, helping employees manage personal and family responsibilities, and engaged employees may work more efficiently, so that work encroaches less on their personal time (Greenhaus & Powell, 2006). Therefore, engagement is expected to be associated with a better balance between work and non-work demands.

Inggamara et al. (2022) analyzed data from the Sixth European Working Conditions Survey, encompassing 43,850 European respondents. According to their research, work engagement positively correlates with social support and WLB. The study highlights the importance of a supportive work environment for raising employee engagement and, in turn, WLB. Because few previous studies have tested the relationship between workforce engagement and work–life balance, the following hypothesis is proposed:

H4: Workforce engagement is positively associated with work–life balance.

2.5. Work–life balance and workforce mental health

Work–life balance (WLB) has emerged as a critical factor influencing workforce mental health. Based on the JD-R model, WLB represents a positive personal and contextual resource that helps employees recover from job demands and maintain psychological well-being. By reducing work-related strain and enabling better management of personal and work responsibilities, improved WLB is expected to be associated with better workforce mental health.

From the perspective of work–family enrichment theory, a good balance between work and non-work roles allows the resources and positive affect generated in each role to support functioning in the other, which is expected to be reflected in better mental health at the workplace.

A growing body of empirical research supports the hypothesis that WLB is positively associated with mental health, highlighting its significance in organizational behavior and employee well-being. Liswandi and Muhammad (2023) conducted a systematic review that examined the relationship between WLB and employee mental health in several nations, including Malaysia, South Korea, India, and Indonesia. According to this study, there was a positive correlation between WLB and mental health indicators, such as psychological well-being, resilience, life satisfaction, and job performance. On the contrary, poor WLB was linked with mental health issues such as depression, anxiety, burnout, and work-related stress. This comprehensive analysis emphasizes the importance of WLB in preserving and improving employee mental health in various work environments.

Additional support is offered by Zhang et al. (2024), who examined the mechanisms linking WLB and mental health among nurses in Pakistan. They found that WLB was positively related to psychological capital and job satisfaction, which in turn were related to better mental health. As shown in the sequential mediation result, psychological capital and job satisfaction mediate the relationship between WLB and mental health. This suggests that a positive WLB contributes to enhancing positive psychological resources and job satisfaction, leading to better mental health.

H5: Work–life balance is positively associated with workforce mental health.

2.6. The mediating role of work–life balance

Integrating the two theories, workforce engagement may be associated with workforce mental health not only directly, as proposed by the JD-R motivational process, but also indirectly through work–life balance, as suggested by work–family enrichment theory: engaged employees may transfer a sense of connection and positive affect to the non-work domain, which supports work–life balance, and a better work–life balance is, in turn, expected to be associated with better mental health. Specifically, engagement may help employees maintain a work–life balance. An improved work–life balance is expected to be associated with better mental health by supporting recovery from work. Prior studies have shown that work–life balance can operate as a mediating mechanism between work-related resources and well-being outcomes (Stankevičienė et al., 2021; Andrlić et al., 2025).

Andrlić et al. (2025) studied the mediating role of WLB in the relationship between organizational support and work engagement among female IT employees in Kerala, India. They found that the association between organizational support and work engagement was partially mediated by the WLB. This study highlights those organizational processes may be important for WLB, which is associated with employee's engagement and health.

Moreover, Stankevičienė et al. (2021) examined the mediating effect of WLB on the relationship between work culture and employee well-being in Lithuania. According to the study, work culture elements such as supportive

supervision and temporal flexibility significantly impact WLB, which in turn affects employee well-being. These results imply that encouraging a work environment that supports WLB can benefit employees' mental health. As these studies indicate that WLB can play a mediating role, the following hypothesis is proposed:

H6: Work-life balance mediates the relationship between workforce engagement and mental health.

2.7. Social support from peers and workforce mental health

Peer social support is widely regarded as important for workforce mental health. Peer support includes instrumental, emotional, and informational help from peers, which promotes a sense of community and reduces feelings of loneliness. This support system is essential for reducing stress and improving workers' psychological health. In the JD-R model, peer support is a social job resource that can reduce stress and support coping.

Research has shown that peer support is associated with better workplace mental health outcomes. For example, according to Myrick and Del Vecchio (2016), peer support has become essential for wellness coaching, illness self-management, and linking individuals to health and community resources. In addition to improving patient outcomes, such support promotes a sense of community and shared experience, both of which are critical for mental health.

Furthermore, a national survey of peer providers revealed that most of their work involves offering direct peer support, including emotional encouragement, shared experiences, and guidance in navigating recovery (Cronise et al., 2016). Such direct engagement has been linked to improvements in self-esteem, reduced feelings of isolation, and increased motivation among those receiving support. Based on these findings, the following hypothesis is proposed:

H7: Social support from peers is directly associated with workforce mental health.

2.8. Knowledge gaps

Despite growing research on these topics, three gaps remain. First, limited attention has been given to tech-savvy leadership as a supervisor-level construct and its relationship with workforce engagement in IT-intensive environments, although digital leadership has been examined extensively (Hooi & Chan, 2023; Li et al., 2024). Second, previous studies have mainly examined individual relationships (e.g., Kundu et al., 2020 ; Majid et al., 2023; Zhang et al., 2024) rather than a framework in which workforce engagement links workplace resources with work–life balance and workforce mental health. Third, most evidence comes from developed economies or from India and Pakistan and may not reflect Bangladesh's rapidly growing IT sector. Finally, a methodological gap remains in previous studies, which have primarily focused on direct relationships among workplace factors and employee outcomes. Such approaches provide a limited understanding of complex mechanisms and the relative importance of different workplace conditions. This study addresses this limitation by employing PLS-SEM to examine direct and indirect relationships.

2.9. Research questions

This study focuses on this knowledge gap and addresses the broad research question of how tech-savvy leadership and behavioral clarity are associated with workforce engagement and, in turn, workforce mental health in Bangladesh's rapidly expanding IT industry. It also examines the associations of work–life balance and peer support with workforce mental health and the mediating role of work–life balance in the relationship between workforce engagement and workforce mental health.

The specific research questions of the study are as follows:

1: How is tech-savvy leadership associated with workforce engagement?

2: How is behavioral clarity associated with workforce engagement?

3: To what extent is workforce engagement associated with workforce mental health?

4: To what extent is workforce engagement associated with work–life balance?

5: How is work–life balance associated with workforce mental health?

6: Does work–life balance mediate the association between workforce engagement and workforce mental health?

7: How is social support from peers associated with workforce mental health?

Conceptual framework and theoretical underpinning

3.1. Conceptual framework

Based on the literature review, identified gaps, and proposed hypotheses, this study developed an integrated framework. The framework identified tech-savvy leadership and behavioral clarity as the two key predictors of workforce engagement and indirectly of workforce mental health. Furthermore, the model examined whether workforce engagement was associated with work–life balance, which in turn was associated with workforce mental health. It also considered the role of peer social support as a direct correlate of mental health. Finally, the model suggested that work–life balance mediates the relationship between workforce engagement and mental health. All these relationships were examined through the lens of the motivational process of the JD-R model, complemented by work–family enrichment theory for the relationships involving work–life balance. By addressing construct, theoretical, contextual, and methodological gaps, this study contributes to advancing knowledge on sustainable employee well-being in emerging digital economies.

3.2. Theoretical underpinning of the conceptual framework: job demands–resources model and work–family enrichment theory

The conceptual framework draws on two complementary theories: the job demands–resources (JD-R) model, which explains the relationships within the work domain, and work–family enrichment theory, which explains how work experiences extend to employees' lives outside work. Each theory is described below, followed by an explanation of how the two together underpin the conceptual model.

3.2.1 Job demands–resources model

The JD-R model, introduced by Demerouti et al. (2001), explains how workplace characteristics influence employee well-being through two categories: job demands and job resources. Job demands refer to aspects of work that require sustained physical or psychological effort and may lead to strain, whereas job resources are workplace factors that help employees achieve goals, reduce work-related costs, and promote personal growth (Demerouti et al., 2001; Schaufeli, 2017).

The JD-R model proposes two psychological processes. The health impairment process occurs when excessive job demands deplete employees' energy and contribute to negative outcomes, whereas the motivational process suggests that job resources enhance work engagement and generate positive employee outcomes (Schaufeli & Bakker, 2004; Schaufeli, 2017).

As illustrated in **Figure 1**, this study applies the motivational pathway of the JD-R model by conceptualizing tech-savvy leadership, behavioral clarity, and

social support from peers as job resources. These resources provide employees with technological guidance, clear expectations, and interpersonal support, which are expected to be associated with higher workforce engagement (Schaufeli, 2017).

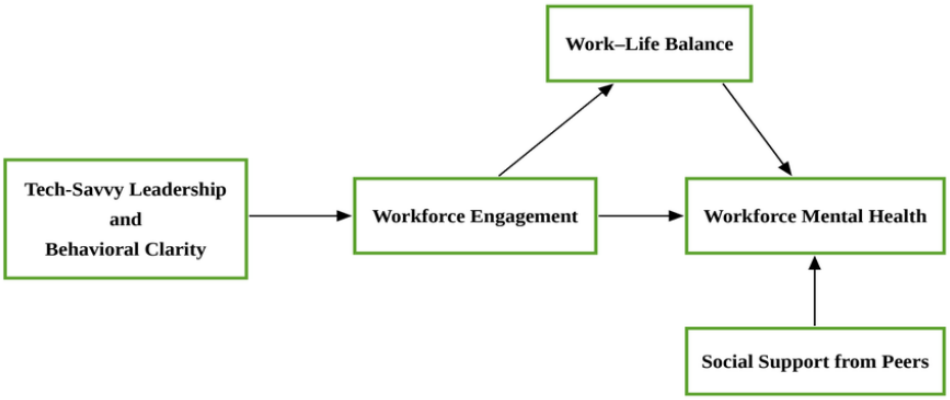


Figure 1. Conceptual model.

This study examined only the motivational process of the JD-R model, in which job resources are associated with engagement and well-being (Bakker & Demerouti, 2007). Job demands such as workload, role ambiguity, digital fatigue, and deadline pressure were not measured. Consequently, the health-impairment process and the potential buffering role of job resources against job demands are outside the scope of this study, and the findings should not be interpreted as a test of the full JD-R model.

Within this framework, tech-savvy leadership, behavioral clarity, and social support from peers are treated as job resources; workforce engagement represents the motivational state through which job resources are expected to relate to outcomes; work–life balance represents a condition linking the work and non-work domains; and workforce mental health represents the well-being outcome of the motivational process.

Workforce engagement represents the motivational mechanism through which job resources are related to employee outcomes. Employees with higher engagement are more likely to feel supported, valued, and connected in their work, which is expected to be associated with better workforce mental health (Schaufeli & Bakker, 2004) and, through the enrichment mechanism described below, with better work–life balance.

3.2.2 Work–family enrichment theory

Work–family enrichment theory (Greenhaus & Powell, 2006) addresses the positive aspects of the interface between work and non-work life. It defines enrichment as the extent to which experiences in one role improve the quality of life in the other role, in contrast to the work–family conflict perspective, which emphasizes the competing demands of the two domains. According to the theory, participation in a role generates five types of resources: skills and perspectives, psychological and physical resources, social capital resources, flexibility, and material resources.

These resources can enrich other roles through two paths. Through the instrumental path, a resource generated in one role is transferred directly to the other role and improves functioning there; through the affective path, a resource generated in one role produces positive affect, which in turn improves functioning in the other role. Enrichment can operate in both directions, from work to family and from family to work. Therefore, the theory complements the JD-R model: whereas the JD-R model explains how job resources are related to engagement

and well-being within the work domain, it does not specify how experiences at work extend to employees' lives outside work, which is the focus of work–family enrichment theory.

3.3. How the two theories explain the conceptual model

The two theories play complementary roles in the conceptual model (**Figure 1**). The JD-R motivational process explains the relationships within the work domain: tech-savvy leadership and behavioral clarity, as job resources, are expected to be associated with workforce engagement (H1 and H2; Sections 2.1 and 2.2); engagement is expected to be associated with workforce mental health (H3; Section 2.3); and social support from peers is a further job resource that is expected to be directly associated with workforce mental health (H7; Section 2.7). Work–family enrichment theory explains the relationships that cross the boundaries between work and non-work lives. Through the affective path, the sense of connection and positive affect associated with engagement may spill over into the non-work domain and support work–life balance (H4; Section 2.4). A good balance between work and non-work roles allows the resources generated in each role to support functioning in the other, which is expected to be associated with better mental health among workers (H5; Section 2.5). Therefore, work–life balance may transmit part of the association between engagement and mental health (H6; Section 2.6). Because the theory treats enrichment as bidirectional, it also accounts for the reverse direction from work–life balance to engagement, as reported in the literature (Inggamara et al., 2022). Therefore, H4 was tested as an association, and an alternative model with the reverse direction was also examined.

Therefore, the proposed conceptual model (**Figure 1**) reflects the JD-R motivational process, complemented by work–family enrichment theory, in which workplace resources are associated with workforce engagement, which, in turn, is associated with work–life balance and workforce mental health. Social support from peers is treated as an additional job resource that helps employees manage workplace challenges (Schaufeli, 2017) and is therefore expected to be directly associated with workforce mental health.

4. Method

4.1. Questionnaire development

The questionnaire used in this study was developed using a three-pronged approach, including a literature review, expert interviews, and pilot testing.

The first step involved reviewing the pertinent literature on the study variables and identifying questions related to these variables that were examined in earlier research. These questions were selected because they have been tested in various contexts worldwide and produced reliable statistical results. The authors then adapted and tailored the most relevant questions to create a questionnaire suitable for the Bangladeshi context.

In the second step, the questionnaire was reviewed by experts, including professors from Dhaka University, the University of West London, and the Asian University of Technology, and senior public sector leaders in Bangladesh, including secretaries of the Ministries of Planning and Public Administration. These professionals provided valuable feedback and insights that were incorporated into the questionnaire.

In the third stage, a pilot test was conducted from January to mid-February 2025 with 50 IT professionals (network engineers, software developers, database administrators, and managers) from approximately 10 organizations in Bangladesh (60% male, 40% female; work experience of 3–12 years). The pilot assessed whether the items were intelligible and easy to complete; participants took approximately 10–15 minutes to complete the questionnaire. The respondents also

provided feedback on the questionnaire, which the authors used to ensure that the questionnaire was free of wording bias, covered the essential aspects of the study variables, and was easily understandable to respondents. Based on this feedback, two changes were made. First, because participants were uncertain whether to answer about their current or a previous workplace, the instructions were revised to specify that all responses should refer to the respondent's current workplace. Second, because the layout caused some participants to miss response options, the spacing and alignment of the response options were adjusted to improve readability. The responses of the 50 pilot participants were retained in the final sample of 419 respondents because the wording of the measurement items was not changed. As a result, the dataset does not identify which responses came from the pilot. The questionnaire consisted of two sections. The first section collected respondents' demographic information. The second section included pertinent questions or statements related to the study variables, measured using a 7-point Likert scale to quantify the variables for statistical analysis.

Finally, the authors collected data using convenience sampling from IT companies in Bangladesh. This approach aimed to ensure that the respondents worked in IT firms or in the IT divisions of other organizations. The organizations approached included Express Systems Limited (ESL), Toggi Services, Bangladesh Japan Information Technology (BJIT) Limited, Southtech Limited, Kaz Software, REVE Systems, Nascenia, Riseup Labs, Dream71 Bangladesh Ltd, Workspace Infotech Limited, and Vivasoft Limited, as well as financial institutions such as BRAC Bank, City Bank, and Eastern Bank Limited (EBL). Bank respondents were employees of the banks' IT divisions only, working in software development, system administration, and network, database, and data roles comparable to those in IT companies. Because the survey link was also shared in professional WhatsApp groups, respondents were not limited to the organizations listed above, and their organization names were not recorded.

4.2. Data collection procedure

A systematic approach was applied to data collection to ensure the reliability and integrity of the data and to capture a range of perspectives from professionals in Bangladesh's IT industry. A convenience sampling method was used to reach IT professionals across different organizational levels and levels of seniority; as a non-probability approach, it does not ensure that the sample is representative of the IT workforce in Bangladesh. Online tools were employed for data collection over approximately two and a half months.

Respondents were categorized based on their job positions (i.e., managers, team leaders, and subordinates) and years of work experience. The sample size was determined based on contemporary recommendations for partial least squares structural equation modeling (PLS-SEM). Although the traditional 10-times rule provides a preliminary estimation, recent studies suggest that more rigorous approaches, such as the inverse square root and gamma-exponential methods, provide more reliable sample size assessments (Kock & Hadaya, 2018; Hair et al., 2022). Considering the three structural paths directed toward the endogenous construct with the highest number of incoming relationships, the collected 419 responses exceeded the recommended minimum requirement and provided sufficient statistical power for the PLS-SEM analysis for all paths except the smallest ($\beta = 0.104$; required $n = 571$; see Section 5.9). The collected data included demographic information, such as age, gender, education, and work experience, along with responses measuring the study's independent, mediating, dependent, and control variables.

The main data collection took place from mid-February to April 2025, after the pilot test was completed. This period provided sufficient time for survey

distribution and follow-up reminders to achieve an adequate response rate. Data were collected using online surveys administered through Google Forms.

The procedure began with obtaining permission from contact persons in the participating organizations and informed consent from individual respondents. The survey link was then distributed via organizational contacts and shared in various WhatsApp groups of IT professionals in Bangladesh. Reminders were sent every two weeks to improve participation. Throughout the process, strict confidentiality was maintained. In total, 419 responses were received, including 50 pilot responses. Because the survey link was distributed through organizational contacts and open professional groups, the number of people who received the link could not be determined, and the response rate could not be calculated. All substantive questionnaire items were set as required in Google Forms, and inspection of the exported dataset confirmed that there were no missing values for the study variables. No responses were excluded, and all 419 responses were retained for analysis. To ensure that respondents were eligible, the questionnaire began with a screening question asking whether they performed technology-related work in their workplace; only respondents who answered "yes" could proceed to the main sections of the questionnaire. The job positions reported by respondents were predominantly technical IT roles (**Table 2**).

4.3. Measurement items

The initial part of the survey collected demographic data, including respondents' age, gender, education, total work experience, experience in the current organization, type of employment, current position, and work location (**Table 2**). The subsequent section evaluates the study's independent and dependent variables, with items developed using the three-pronged approach described above. **Table 1** details the measurement of each variable and the references from which the items were obtained.

Table 1. Measurement items for constructs were derived from, or developed based on, the existing literature, refined through expert feedback, and validated via pilot testing.

Constructs (Adapted from or Developed Based on the Literature)	Measurement Items	Primary Source(s)
Tech-savvy Leadership	My manager demonstrates a strong understanding of the technologies relevant to our work processes. My manager effectively identifies and applies appropriate technologies to improve work processes and team performance. My manager guides employees to adapt to and effectively use new technologies in the workplace.	McLeod et al. (2015) Cortellazzo et al. (2019) Kane et al. (2019)
Behavioral Clarity	The instructions and expectations provided by the manager are clear. Unclear communication practices from my manager often lead to workplace stress. My manager provides clear goals and deadlines for my tasks.	Locke & Latham, 1990
Workforce Engagement	I feel supported and empowered to contribute meaningfully to my organization's goals. I feel valued and motivated to share my ideas and perspectives at the workplace. I feel a strong sense of connection and belonging to my team.	Author-developed; conceptual basis: Graen & Uhl-Bien, 1995
Work-Life Balance	I can effectively balance my work and personal life. I have enough time for personal and family activities outside work.	Kalliath & Kalliath, 2012; Haar & Roche, 2010
Social Support from Peers	My colleagues are supportive in helping me manage the work-related challenges. Peer support improves my ability to manage stress at work.	Karatepe & Tekinkus,2006; Blau, 1964

Continued table:

Constructs (Adapted from or Developed Based on the Literature)	Measurement Items	Primary Source(s)
Workforce Mental Health	I feel psychologically supported and can maintain my mental well-being at work. My work provides me with a sense of purpose and accomplishment without negatively affecting my mental health. My organization creates an environment in which employees' mental health and well-being are valued and supported.	Author-developed; conceptual basis: World Health Organization, 2022; Judge et al., 2001

Note: Workforce mental health is defined as positive, work-related mental health, following the World Health Organization (2022). Its three items capture the ability to maintain psychological well-being at work, a sense of purpose and accomplishment, and perceived organizational support for mental health, rather than clinical symptoms. The three behavioral clarity items capture clear instructions, clear goals and deadlines, and the absence of ambiguous communication. The negatively worded item was reverse-scored before analysis, so that higher scores indicate greater clarity.

All constructs were grounded in the literature, and all items were subsequently evaluated by experts from regulatory authorities and academia to ensure their suitability for the Bangladeshi context. Adjustments were finalized based on pilot testing feedback from IT professionals to enhance the clarity and relevance of the questionnaire. Respondents rated the measurement items using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The workforce engagement and workforce mental health items were developed by the authors for this study. The engagement items, informed by leader–member exchange research (Graen & Uhl-Bien, 1995), capture support and empowerment, voice, and belonging, reflecting the participative aspects of engagement rather than vigor, dedication, and absorption. The mental health items, informed by the World Health Organization (2022) and Judge et al. (2001), capture psychological well-being at work, purpose and accomplishment, and perceived organizational support for mental health, and therefore also reflect perceived support and work-related meaning. These items were reviewed by academic and industry experts and pilot-tested before the main data collection (see **Supplementary Table 1**).

5. Results

5.1. Demographic characteristics

The demographic characteristics of the respondents are presented in **Table 2** below. **Table 2** shows that the study sample consisted of a diverse workforce, with 82.4% of participants aged 18–40 years (41.3% aged 18–30 and 41.1% aged 31–40) and 3.8% over 50 years. The gender distribution included 56.6% males and 43.4% females. Educationally, 96% held Bachelor's (51.6%) or Master's degrees (44.4%), with 0.5% having doctoral degrees. Work experience varied, with 24.1% reporting over 10 years of total experience, while 65.4% worked in their current organization for three years or less. Employment was primarily full-time (89.7%), with smaller proportions of interns (1.9%), contract workers (1.7%), freelancers (4.3%), and temporary employees (2.4%). Job roles were diverse, including significant representation in technical positions such as Senior Manager/Lead Developer and Software Engineer/Developer (15.5% each) and Network Engineer (10.5%). Most participants worked on-site (94.5%), with 4.3% in hybrid and 1.2% in remote settings.

Table 2. Demographic profile of the respondents

Demographic Characteristics			
Variables	**Description**	**Number**	**Percentage**
Age of Employee	18-30 years	173	41.3
	31-40 years	172	41.1
	41-50 years	58	13.8
	Above 50 years	16	3.8
Gender	Male	237	56.6
	Female	182	43.4
Educational level	High School or Diploma	15	3.6
	Bachelor's Degree	216	51.6
	Master's Degree	186	44.4
	Doctoral Degree (PhD, EdD)	2	0.5
Total Working Experience	Less than 1 year	73	17.4
	1-3 years	61	14.6
	4-6 years	93	22.2
	7-10 years	91	21.7
	More than 10 years	101	24.1
Experience in Current Organization	Less than 1 year	137	32.7
	1-3 years	137	32.7
	4-6 years	87	20.8
	7-10 years	43	10.3
	More than 10 years	15	3.6
Type of Employment	Full-time	376	89.7
	Intern	8	1.9
	Contract	7	1.7
	Freelance	18	4.3
	Temporary	10	2.4
Current Position	Senior Manager/Lead Developer	65	15.5
	Manager	57	13.6
	Software Engineer/Software Developer/Web Developer	65	15.5
	Senior Management	2	0.5
	IT Specialist	2	0.5
	Junior/Entry-level Employee	1	0.2
	Business Analyst	33	7.9
	UX Designer	34	8.1
	Product Manager	31	7.4
	Network Engineer	44	10.5
	System Administrator	31	7.4
	Lead Software Engineer	27	6.4
	Data Analyst	27	6.4
Location	On-site	396	94.5
	Hybrid	18	4.3
	Remote	5	1.2

5.2. PLS-SEM model

To examine the hypotheses outlined in the conceptual framework, two distinct SmartPLS 4 outputs were produced, illustrated in **Figures 2 and 3**. **Figure 2** displays the PLS-SEM algorithm model, highlighting the path coefficients (β values), which reflect the strength and direction of the relationships

among tech-savvy leadership, behavioral clarity, workforce engagement, work–life balance, social support from peers, and workforce mental health.

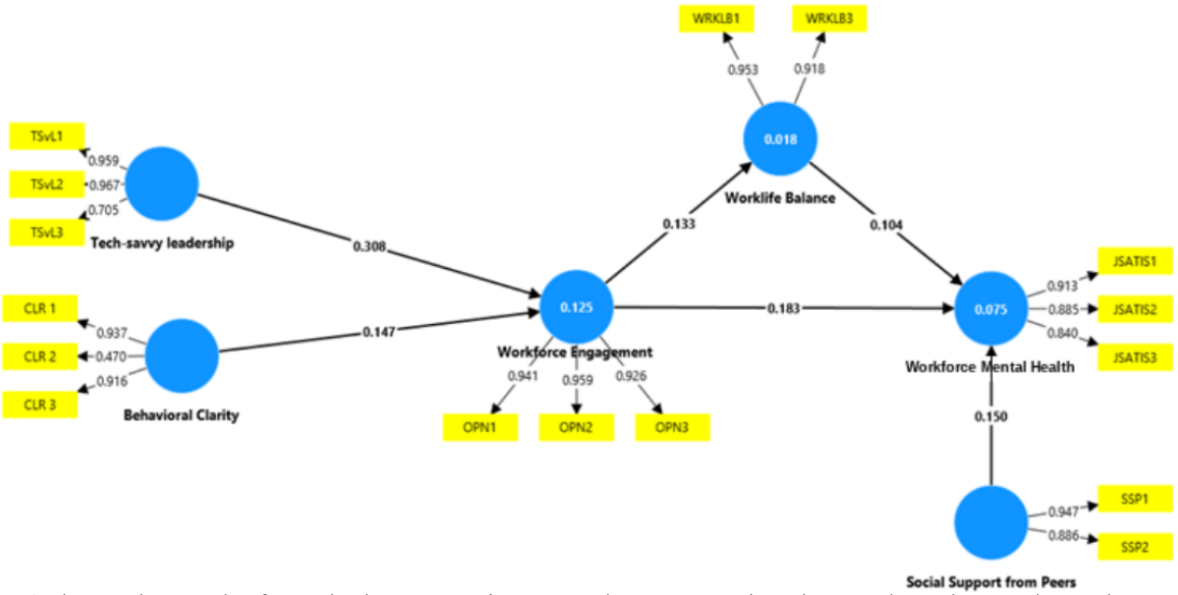


Figure 3 shows the results from the bootstrapping procedure, presenting the p-values that evaluate the statistical significance of the model's paths. This figure demonstrates how tech-savvy leadership, behavioral clarity, workforce engagement, work–life balance, and social support from peers are associated with workforce mental health.

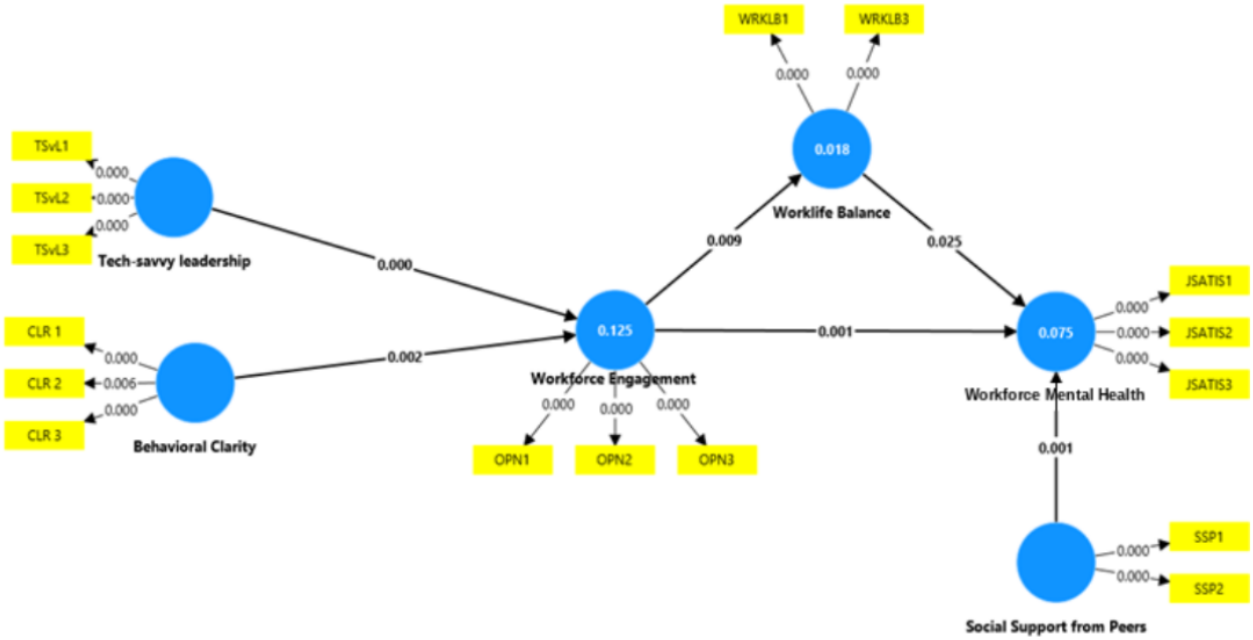


Figure 3. PLS-SEM bootstrapping model

5.3. Reliability and validity

To evaluate the reliability and validity of the constructs in the study, several psychometric parameters were employed: Cronbach's alpha (α) for internal consistency reliability, composite reliability (rho_a and rho_c) for assessing construct reliability, and average variance extracted (AVE) for convergent validity. Summary statistics for the reliability and validity of the study constructs are shown in **Table 3a**.

In **Table 3a**, Cronbach's alpha (α) values for the constructs range from 0.728 to 0.937 and are therefore above the recommended cut-off value of 0.700, demonstrating acceptable to excellent internal consistency (Hair et al., 2016).

Composite reliability (rho_a) varies from 0.856 to 0.959 and rho_c from 0.836 to 0.960, which exceed the 0.700 threshold, indicating strong construct reliability (Kline, 2015). The AVE estimates support convergent validity because they all exceed the 0.500 criterion, i.e., from 0.646 to 0.888 (Hair et al., 2016; Agresti & Finlay, 2008). Taken together, these findings support the reliability and validity of all six constructs.

Table 3a. Construct reliability and validity overview

Table 3 a. Construct reliability and validity overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral clarity (CLR)	0.728	0.908	0.836	0.646
Social Support from Peers (SSP)	0.817	0.896	0.914	0.841
Tech-savvy leadership (TSvL)	0.862	0.959	0.914	0.784
Workforce Mental Health (JSATIS)	0.854	0.856	0.912	0.775
Workforce Engagement (OPN)	0.937	0.939	0.96	0.888
Work–Life Balance (WRKLB)	0.86	0.905	0.934	0.876

Table 3b presents the indicator loadings, their 95% bootstrap confidence intervals, and the indicator-level variance inflation factors (VIFs). All loadings were statistically significant ($p < 0.01$). Apart from CLR 2, loadings ranged from 0.705 to 0.967, and all except TSvL3 (0.705, marginally below) exceeded the recommended threshold of 0.708 (Hair et al., 2019). CLR 2, the negatively worded behavioral clarity item, had a loading of 0.470. Indicators with loadings between 0.40 and 0.708 may be retained when the construct's composite reliability and AVE exceed their thresholds (Hair et al., 2022); because behavioral clarity met these criteria ($\rho c = 0.836$; AVE $= 0.646$), CLR 2 was retained, although its wide confidence interval indicates that it is a comparatively weak indicator. Indicator VIFs ranged from 1.150 to 6.657. The values above 5 for TSvL1 (6.170), TSvL2 (6.657), and OPN2 (5.186) indicate substantial redundancy among items of the same reflective construct; this does not bias the structural estimates, for which collinearity among predictor constructs is the relevant criterion (see Section 5.7). In particular, TSvL1 and TSvL2 are very highly correlated ($r = 0.915$), indicating that they capture closely overlapping aspects of tech-savvy leadership, so that the construct rests mainly on two distinct facets. In addition, two items refer partly to stress CLR 2: unclear communication leads to workplace stress; SSP2: peer support improves the ability to handle stress at work), which introduces some content overlap with strain-related experiences; these features are acknowledged as limitations.

Table 3 b. Indicator loadings and collinearity statistics

Construct	Indicator	Loading	95% CI	VIF
Tech-savvy leadership	TSvL1	0.959	[0.941, 0.974]	6.17
	TSvL2	0.967	[0.953, 0.976]	6.657
	TSvL3	0.705	[0.605, 0.775]	1.503
Behavioral clarity	CLR 1	0.937	[0.862, 0.969]	2.267

Continued table:

Construct	Indicator	Loading	95% CI	VIF
	CLR 2	0.47	[0.014, 0.700]	1.15
	CLR 3	0.916	[0.804, 0.946]	2.318
Workforce engagement	OPN1	0.941	[0.922, 0.955]	4.321
	OPN2	0.959	[0.949, 0.968]	5.186
	OPN3	0.926	[0.901, 0.945]	3.537
Work–life balance	WRKLB1	0.953	[0.919, 0.983]	2.324
	WRKLB3	0.918	[0.852, 0.951]	2.324
Social support from peers	SSP1	0.947	[0.899, 0.991]	1.913
	SSP2	0.886	[0.734, 0.942]	1.913
Workforce mental health	JSATIS1	0.913	[0.881, 0.937]	2.742
	JSATIS2	0.885	[0.840, 0.919]	2.298
	JSATIS3	0.84	[0.788, 0.880]	1.837

Note. Loadings and 95% percentile confidence intervals were based on bootstrapping with 5,000 subsamples. VIF = variance inflation factor.

The three workforce mental health items loaded strongly on their construct (0.840–0.913), with satisfactory reliability ($\alpha = 0.854$; $\rho c = 0.912$) and convergent validity (AVE $= 0.775$), and the Heterotrait-Monotrait Ratio values between workforce mental health and the other constructs were low (0.113–0.238), supporting its discriminant validity. Because the third item refers to the organization's concern for employees' mental health rather than the respondent's own state, the model was also re-estimated without this item as a sensitivity analysis. All path coefficients remained virtually unchanged and significant (e.g., workforce engagement → workforce mental health: 0.185 vs. 0.183; work–life balance → workforce mental health: 0.101 vs. 0.104; social support from peers → workforce mental health: 0.133 vs. 0.150).

5.4. Common method bias

Because all variables were measured through a single self-report questionnaire completed by the same respondents at one point in time, common method bias (CMB) was addressed through procedural and statistical remedies (Podsakoff et al., 2003). Participation was voluntary and anonymous: respondents were informed that their responses would be anonymous, and no names, email addresses, or other identifying information were collected, which reduces evaluation apprehension and socially desirable responding. In addition, the items for different constructs were presented in separate sections of the questionnaire, which created a degree of psychological separation between the measurement of predictor and outcome variables, and item wording was refined through expert review and pilot testing to reduce ambiguity. However, the instructions did not state that there were no right or wrong answers; therefore, not all recommended procedural remedies were applied. Statistically, a full collinearity assessment was conducted using the latent variable scores from the PLS-SEM estimation (Kock, 2015): each construct was regressed on all other constructs, and the resulting variance inflation factors ranged from 1.04 to 1.18, well below the threshold of 3.3, indicating that the model was not substantially affected by CMB. As supplementary evidence, Harman's single-factor test (unrotated principal component analysis of all 16 indicators) showed that the first factor accounted for 24.3% of the total variance, well below the 50% threshold, and six factors had eigenvalues greater than 1; however, this test is regarded as a weak diagnostic (Podsakoff et al., 2003). Finally, although tech-savvy leadership, behavioral clarity, and workforce engagement are all reported by employees with reference to their immediate work environment, their HTMT values were low

(0.120–0.339), which argues against a general halo effect in respondents' ratings.

5.5. Model fit

Table 4 presents the model fit indices. SRMR values below 0.08 indicate a good approximate fit, whereas d_ULS and d_G have no fixed thresholds and are assessed against bootstrap-based reference values (Henseler, Hubona, & Ray, 2016). The SRMR was 0.043 for the saturated model and 0.054 for the estimated model, both indicating an acceptable approximate fit. To test the exact model fit, SRMR, d_ULS, and d_G were compared with their bootstrap-based (5,000 samples) 95% and 99% quantiles (HI95 and HI99). For the saturated model, all three measures were below their HI95 values (SRMR: 0.043 vs. 0.044; d_ULS: 0.257 vs. 0.265; d_G: 0.235 vs. 0.277). For the estimated model, d_G was below its HI95 value (0.240 vs. 0.280), whereas SRMR (0.054) and d_ULS (0.396) exceeded their HI95 values (0.051 and 0.359) but remained below their HI99 values (0.059 and 0.481). The exact fit of the estimated model was therefore rejected at the 5% level on SRMR and d_ULS, but not at the 1% level. The Normed Fit Index of 0.833 is below the commonly cited threshold of 0.90 and, like the chi-square value (646.672), is reported for completeness only. Because global model fit measures in PLS-SEM remain debated, the model is evaluated mainly on the quality of the measurement model and the explanatory and predictive power of the structural model (Hair et al., 2019; Hair et al., 2022).

Table 4. SEM Model 1 fit summary

	Saturated model	Estimated model
SRMR	0.043	0.054
d_ULS	0.257	0.396
d_G	0.235	0.24
Chi-square	636.657	646.672
NFI	0.836	0.833

5.6. Discriminant validity

Tables 5a and 5b show the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio used to assess discriminant validity. The Fornell–Larcker criterion compares the square root of each construct's Average Variance Extracted (AVE) to its correlations with other constructs, ensuring that the former is higher (Fornell & Larcker, 1981). The HTMT ratio is not an ordinary inter-construct correlation; it is the mean of the correlations between indicators of different constructs (heterotrait–heteromethod correlations) relative to the geometric mean of the average correlations among indicators of the same construct (monotrait–heteromethod correlations), with values below 0.85 (conservative) or 0.90 indicating discriminant validity (Henseler et al., 2015; Hair et al., 2019). **Table 5a** summarizes both tests, showing that the square roots of AVE (diagonal values: 0.804, 0.917, 0.885, 0.880, 0.942, 0.936) exceed the latent variable correlations (values above the diagonal, ranging from 0.007 to 0.321) for all constructs, including behavioral clarity, social support from peers, tech-savvy leadership, workforce mental health, workforce engagement, and work–life balance. Additionally, all HTMT ratios (values below the diagonal) range from 0.020 to 0.339, well below the conservative threshold of 0.85. As recommended, the HTMT ratios were also assessed using bootstrap confidence intervals (5,000 subsamples; **Table 5b**); the upper bounds of all 95% confidence intervals were well below 0.85 (maximum = 0.462), confirming discriminant validity.

Table 5 a. Discriminant validity –Fornell–Larcker criterion (diagonal and above) and HTMT ratios (below the diagonal)

	Behavioral clarity	Social Support from Peers	Tech-savvy leadership	Workforce Mental Health	Workforce Engagement	Work–Life Balance
Behavioral clarity	0.804	0.096	0.089	0.096	0.175	0.064
Social Support from Peers	0.115	0.917	0.014	0.16	0.007	0.085
Tech-savvy leadership	0.12	0.02	0.885	0.2	0.321	0.073
Workforce Mental Health	0.113	0.186	0.238	0.88	0.198	0.141
Workforce Engagement	0.188	0.027	0.339	0.219	0.942	0.133
Work–Life Balance	0.085	0.102	0.093	0.164	0.144	0.936

Note. The values on the diagonal are the square roots of the AVE, and the values above the diagonal are the latent variable correlations (Fornell–Larcker criterion). The values below the diagonal are the heterotrait–monotrait (HTMT) ratios.

Table 5 b. HTMT ratios with 95% bootstrap confidence intervals

Construct pair	HTMT	95% CI [lower, upper]
Social support from peers –Behavioral clarity	0.115	[0.040, 0.243]
Tech-savvy leadership –Behavioral clarity	0.12	[0.054, 0.249]
Tech-savvy leadership –Social support from peers	0.02	[0.020, 0.141]
Workforce mental health –Behavioral clarity	0.113	[0.056, 0.246]
Workforce mental health –Social support from peers	0.186	[0.076, 0.305]
Workforce mental health –Tech-savvy leadership	0.238	[0.119, 0.362]
Workforce engagement –Behavioral clarity	0.188	[0.083, 0.323]
Workforce engagement –Social support from peers	0.027	[0.022, 0.139]
Workforce engagement –Tech-savvy leadership	0.339	[0.211, 0.462]
Workforce engagement –Workforce mental health	0.219	[0.101, 0.337]
Work–life balance –Behavioral clarity	0.085	[0.042, 0.190]
Work–life balance –Social support from peers	0.102	[0.024, 0.220]
Work–life balance –Tech-savvy leadership	0.093	[0.041, 0.190]
Work–life balance –Workforce mental health	0.164	[0.059, 0.271]
Work–life balance –Workforce engagement	0.144	[0.047, 0.257]

Note. The confidence intervals were percentile bootstrap intervals based on 5,000 subsamples.

5.7. Hypothesis testing

The following section presents the results of hypothesis testing and path analysis conducted using PLS-SEM. Because the data are cross-sectional, the path coefficients are interpreted as associations rather than causal effects. **Table 6a** shows the results of the hypothesis testing and path analysis. The PLS-SEM results provide empirical support for most of the proposed relationships in the structural model, with significance determined by t-statistics exceeding 1.96 and p-values below 0.05 (Hair et al., 2022); this criterion, specified in the original analysis plan, was applied to all hypotheses, including the indirect effect (H6). Tech-savvy leadership is significantly and positively associated with workforce engagement ($t = 5.363$, $p < 0.001$). Behavioral clarity is also significantly and positively associated with workforce engagement ($t = 3.046$, $p = 0.002$). Workforce engagement is significantly associated with workforce mental health ($t = 3.397$, $p = 0.001$). Workforce engagement is positively associated with work–life balance ($t = 2.632$, $p = 0.009$). Work–life balance is significantly associated

with workforce mental health ($t = 2.247$, $p = 0.025$). Social support from peers is positively associated with workforce mental health ($t = 3.250$, $p = 0.001$). However, the mediated pathway of workforce engagement through work–life balance to workforce mental health was not supported ($t = 1.558$, $p = 0.119$), as the indirect effect was not statistically significant. The 95% percentile bootstrap confidence interval of the indirect effect [0.001, 0.035] narrowly excluded zero. Because t-based tests and percentile intervals can diverge for indirect effects, whose bootstrap distributions are typically asymmetric, and because the lower bound lay very close to zero, H6 was evaluated using the pre-specified t-test criterion and is reported as not supported. The inference for H6 therefore depends on the method used: the indirect effect is not significant under the t-test criterion, whereas both the percentile and the bias-corrected bootstrap confidence intervals narrowly exclude zero (**Supplementary Table 2**).

Table 6 a. Hypothesis testing and path analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
Tech-savvy leadership - > Workforce Engagement	0.308	0.309	0.057	5.363	< .001	Supported
Behavioral clarity - > Workforce Engagement	0.147	0.155	0.048	3.046	0.002	Supported
Workforce Engagement - > Workforce Mental Health	0.183	0.183	0.054	3.397	0.001	Supported
Workforce Engagement - > Work–Life Balance	0.133	0.135	0.05	2.632	0.009	Supported
Work–Life Balance - > Workforce Mental Health	0.104	0.106	0.046	2.247	0.025	Supported
Social Support from Peers - > Workforce Mental Health	0.15	0.154	0.046	3.25	0.001	Supported
Workforce Engagement - > Work–Life Balance - > Workforce Mental Health	0.014	0.014	0.009	1.558	0.119	Not supported

Note. Hypotheses were evaluated using the pre-specified two-tailed t-test criterion ($p < 0.05$). For H6, the 95% percentile bootstrap confidence interval was [0.001, 0.035] and the bias-corrected interval was [0.002, 0.037]; both narrowly excluded zero, so the inference for H6 depends on the method used (see Section 5.7 and **Supplementary Table 2***).*

The structural model was assessed following Hair et al. (2019). Statistical significance was assessed by bootstrapping with 5,000 subsamples, using two-tailed t-tests ($p < 0.05$), and 95% percentile confidence intervals are also reported. Inner VIF values ranged from 1.000 to 1.025 (**Table 6b**), well below the threshold of 3, indicating no collinearity among predictor constructs. All six direct paths were significant, with 95% confidence intervals that excluded zero. The R^2 values were 0.125 for workforce engagement, 0.018 for work–life balance, and 0.075 for Workforce mental health (adjusted R^2: 0.121, 0.015, and 0.068), indicating weak explanatory power, which is consistent with these outcomes being shaped by many factors not included in the model. The f^2 values ranged from 0.011 to 0.108: the effect of tech-savvy leadership on workforce engagement (0.108) and the effects of behavioral clarity (0.025), workforce engagement on Workforce mental health (0.036), and social support from peers (0.024) were small, whereas the effects of workforce engagement on work–life balance (0.018) and of work–life balance on Workforce mental health (0.011) fell below the conventional threshold of 0.02 for a small effect (Hair et al., 2022).

Table 6 b. Structural model assessment

Path	B	95% CI	f²	VIF
H1: Tech-savvy leadership → Workforce engagement	0.308	[0.198, 0.418]	0.108	1.008
H2: Behavioral clarity → Workforce engagement	0.147	[0.063, 0.250]	0.025	1.008
H3: Workforce engagement → Workforce mental health	0.183	[0.075, 0.289]	0.036	1.018
H4: Workforce engagement → Work–life balance	0.133	[0.038, 0.236]	0.018	1.000
H5: Work–life balance → Workforce mental health	0.104	[0.015, 0.198]	0.011	1.025
H7: Social support from peers → workforce mental health	0.15	[0.069, 0.243]	0.024	1.007

Note. β = standardized path coefficient; CI = percentile bootstrap confidence interval (5,000 subsamples); f² = effect size; VIF = inner variance inflation factor. R² (adjusted R²): workforce engagement 0.125 (0.121); work–life balance 0.018 (0.015); workforce mental health 0.075 (0.068).

5.8. Predictive power (PLSpredict)

Out-of-sample predictive power was assessed with the PLSpredict procedure (Shmueli et al., 2019), using 10 folds and 10 repetitions. All Q^2 predict values for the indicators of the endogenous constructs were positive (0.002–0.113; **Table 6c**), indicating that the model outperforms the naïve mean benchmark. Compared with the linear model (LM) benchmark, PLS-SEM produced lower RMSE values for seven of the eight indicators and an identical value for the eighth, which indicates medium predictive power according to Shmueli et al. (2019). However, the Q^2predict values and the differences in prediction errors were small, so the model's predictive relevance should be regarded as limited.

Table 6 c. Out-of-sample predictive power (PLSpredict)

Construct	Indicator	Q²predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE
Workforce engagement	OPN1	0.079	1.585	1.586	1.195	1.202
	OPN2	0.113	1.524	1.535	1.134	1.134
	OPN3	0.094	1.536	1.551	1.117	1.129
Work–life balance	WRKLB1	0.006	1.851	1.876	1.508	1.510
	WRKLB3	0.002	1.851	1.862	1.577	1.586
Workforce mental health	JSATIS1	0.032	1.715	1.720	1.390	1.383
	JSATIS2	0.032	1.708	1.710	1.421	1.396
	JSATIS3	0.036	1.956	1.956	1.693	1.672

Note. Predictions are based on 10 folds and 10 repetitions. RMSE = root mean squared error; MAE = mean absolute error; LM = linear model benchmark.

5.9. Supplementary analyses

Several supplementary analyses assessed the robustness of the results. First, tech-savvy leadership remained significantly associated with workforce engagement ($\beta = 0.295$, 95% CI [0.179, 0.405]) when transformational leadership ($\alpha = 0.865$) and agile leadership ($\alpha = 0.888$), measured in the same questionnaire, were added as predictors, whereas neither of these was significant ($\beta = 0.060$ and 0.039); removing tech-savvy leadership reduced the R^2 of workforce engagement from 0.130 to 0.046. This analysis was not part of the original hypotheses. Second, excluding two respondents who gave identical scores to all 59 questionnaire items left all direct paths significant; when a

third respondent who gave identical scores to the 16 study items only was also excluded, the path from work–life balance to workforce mental health remained significant but was the weakest path ($\beta = 0.096$, $p = 0.042$; 95% CI [0.008, 0.194]), making it the least robust result. With all three respondents excluded ($n = 416$), the indirect effect for H6 decreased to 0.011 ($t = 1.403$, $p = 0.161$); its 95% percentile bootstrap confidence interval [0.0001, 0.031] only marginally excluded zero (bias-corrected 95% CI [0.001, 0.033]). Third, adding age, gender, education, and work experience as control variables left all paths virtually unchanged (maximum change 0.004), and none of the controls was significant. A summary of these analyses is provided in **Supplementary Table 3**.

Fourth, an alternative model in which work–life balance predicts workforce engagement also yielded a significant path ($\beta = 0.102$, 95% CI [0.017, 0.188]); because the Bayesian Information Criterion differences between the two models were small ($\Delta BIC < 2$), the data do not clearly favor either direction, and the relationship may be reciprocal. Fifth, a Gaussian copula test (Hult et al., 2018) indicated possible endogeneity only for the path from tech-savvy leadership to workforce engagement, which remained positive and significant when the copula term was included (0.675, 95% CI [0.329, 1.027]). Sixth, multigroup analyses by gender, job level, and work experience established full measurement invariance Measurement Invariance of Composite Models; Henseler, Ringle, & Sarstedt, 2016); no gender differences emerged, and the two job-level and experience differences that reached $p = .021$ did not survive a Bonferroni correction. Finally, according to the inverse square root method (Kock & Hadaya, 2018), the sample of 419 provides 80% power at the 5% level for all paths except the smallest ($\beta = 0.104$; required $n = 571$).

5.10. Importance-performance map analysis

The study further conducted an Importance–Performance Map Analysis (IPMA), the results of which are presented below. The importance–performance map analysis (IPMA; **Figure 4**) plots each construct's total effect on workforce mental health (importance) against its average score on a 0–100 scale (performance), indicating which constructs deserve managerial priority (Ringle & Sarstedt, 2016). Workforce engagement has the highest importance (~0.20) and strong performance (~74), and social support from peers combines high importance (~0.14) with solid performance (~70); both are strengths to be maintained. Work–life balance has moderate importance (~0.10) but the lowest performance (~56), making it the main candidate for improvement. Behavioral clarity and tech-savvy leadership perform moderately to well but have lower importance, because they are related to workforce mental health only indirectly through workforce engagement; they should therefore be monitored rather than prioritized (Ringle & Sarstedt, 2016; Hair et al., 2019).

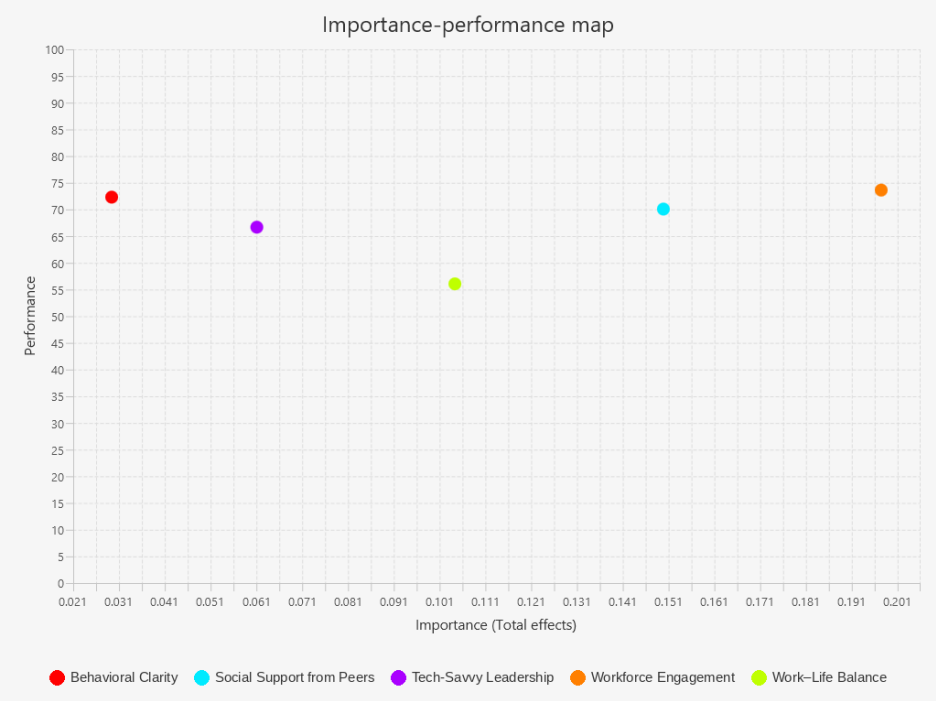


Figure 4. Importance-performance mapping

6. Discussion

6.1. Interpretation of the findings

The results show that the workplace resources examined in this study are positively associated with the engagement and mental health of IT professionals in Bangladesh. Six of the seven hypotheses were supported; the exception was the mediating role of work–life balance (H6), which was not supported under the pre-specified t-test criterion. The findings are discussed below in the order of the hypotheses tested.

First, tech-savvy leadership was positively associated with workforce engagement (H1). This is consistent with research linking leaders' technology orientation to employee engagement (Hooi & Chan, 2023; Li et al., 2024); for example, Li et al. (2024) found that middle managers' digital leadership was positively related to employee work engagement. This study extends this line of research to the supervisor level by examining supervisors' technological competence and their enablement of subordinates' technology use. This may be because, consistent with the JD-R model, such supervisors reduce technology-related uncertainty and help employees feel capable in technology-mediated tasks, although this mechanism was not tested directly. The finding suggests that supervisors' technological competence is a relevant workplace resource for engagement in IT firms.

Behavioral clarity was also positively associated with workforce engagement (H2). This is consistent with evidence from Pakistan and India that role clarity is related to engagement and related outcomes (Kundu et al., 2020; Majid et al., 2023). This may be because, in IT work, where employees often manage multiple roles and changing requirements, clear instructions, goals, and deadlines help employees direct their efforts; this interpretation requires direct testing. This finding suggests that clear expectations are a relevant resource for engagement alongside supervisors' technological competence.

Workforce engagement was positively associated with workforce mental health (H3). This is consistent with Khan et al. (2026), who reported a relationship between engagement practices and employee mental health in the Indian IT sector. This may be because engaged employees experience their work

as more meaningful and feel supported and connected, which is consistent with the positive, work-related view of mental health adopted in this study. In the importance–performance map analysis, workforce engagement also had the largest total association with workforce mental health (**Figure 4**), which suggests that engagement is a central link between workplace resources and mental health in this sample.

Workforce engagement was also positively associated with work–life balance (H4). Previous studies, such as Inggamara et al. (2022), have mainly examined the opposite direction, in which work–life balance is related to engagement; therefore, the present finding adds evidence to a less frequently examined direction. This may be because, as work–family enrichment theory suggests, the sense of connection and positive affect associated with engagement spill over into the life outside work. This finding suggests that engagement is relevant not only to organizational performance but also to employees' work-life balance. However, because the data are cross-sectional, the direction of this association cannot be established; the reverse direction, in which work–life balance supports engagement (Inggamara et al., 2022), is equally plausible, and the two constructs may be reciprocally related. The finding should therefore be interpreted as an association rather than as evidence that engagement improves work–life balance.

Work–life balance was positively associated with workforce mental health (H5). This is consistent with prior findings (Liswandi & Muhammad, 2023; Zhang et al., 2024). This may be because a balanced work–life experience is associated with lower stress and burnout (Liswandi & Muhammad, 2023). This finding suggests that work–life balance is relevant to IT professionals' mental health, in addition to engagement. However, this association weakened but remained significant ($\beta = 0.096$, $p = 0.042$) after excluding three respondents with uniform response patterns (Section 5.9), so it should be interpreted with caution.

In contrast, work–life balance did not significantly mediate the association between workforce engagement and mental health (H6; indirect effect $= 0.014$, $t = 1.558$, $p = 0.119$), even though both component paths were significant. This differs from Andrlić et al. (2025) and Stankevičienė et al. (2021), who reported a mediating role of work–life balance in the relationship between organizational resources and employee engagement or well-being. Although the 95% percentile bootstrap confidence interval [0.001, 0.035] narrowly excluded zero, the pre-specified t-test criterion was not met; the conclusion regarding H6 therefore depends on the inferential method used, and any indirect association through work–life balance is at most very small.

Several factors may explain these results. First, the indirect effect is the product of two small paths ($0.133 \times 0.104 \approx 0.014$), and indirect effects composed of small paths require considerably larger samples for reliable detection (Fritz & MacKinnon, 2007). Therefore, the results do not demonstrate that mediation is absent, but they provide no reliable evidence of its presence. Second, because the direct association between engagement and mental health remained significant, engagement appears to be related to mental health mainly through channels other than work–life balance in this sample. Third, possible reasons for the divergence from previous studies include differences in samples and national contexts, in the variables that work–life balance was proposed to link, and in measurement; in this study, work–life balance was measured using only two items. Finally, an additional untested explanation is that in the Bangladeshi IT industry, employees work long hours under tight deadlines while still facing job insecurity, which may outweigh the benefits of WLB practices. IT workers may also perceive that although WLB initiatives exist in service rules, they are not fully implemented in practice. This finding suggests that, in this sample, work–life balance is better regarded as a

resource in its own right than as a channel through which engagement is related to mental health.

Social support from peers was positively associated with workforce mental health (H7). This is consistent with Myrick and Del Vecchio (2016) and Cronise et al. (2016), who emphasized the role of peer support in mental health outcomes. This may be because peers provide instrumental, emotional, and informational help, which, in terms of the JD-R model, is a social job resource. The present study adds evidence from the IT sector in Bangladesh, and the finding suggests that supportive peer relationships are a relevant resource for IT professionals' mental health.

6.2. Magnitude of the associations

Although most hypotheses were supported, the standardized path coefficients were modest, ranging from 0.104 to 0.308, and the f^2 values (0.011–0.108) indicate small effects for four paths and effects below the conventional threshold for a small effect for the remaining two. These magnitudes are theoretically plausible: workforce mental health is shaped by many factors that were not modeled in this study, including workload, job security, compensation, and life outside work; therefore, each workplace resource is expected to account for only a modest share of its variance. Effects of this size are also common in applied psychology and organizational research, where the empirical distribution of effect sizes is considerably smaller than conventional benchmarks suggest (Bosco et al., 2015). To make the size of these associations more tangible, the importance values from the importance–performance map analysis (**Figure 4**) can be read as the expected change in workforce mental health, on a 0–100 scale, for a one-point change in each construct on the same scale. On this basis, a 10-point higher level of workforce engagement (roughly 0.6 points on the 7-point response scale) is associated with about 2 points higher workforce mental health; the corresponding figures are about 1.5 points for social support from peers, 1 point for work–life balance, 0.6 points for tech-savvy leadership, and 0.3 points for behavioral clarity, whose associations with mental health are indirect. Because the data are cross-sectional, these figures describe associations rather than the expected effects of interventions. Practically, no single resource, such as developing supervisors' technological competence, is likely to be associated with large differences in mental health on its own; combinations of resources are more likely to matter, which is consistent with the resource-accumulation logic of the JD-R model.

6.3. Theoretical implications

The findings contribute to the theory in three ways. First, they extend the motivational pathway of the JD-R model to supervisor-level technological competence: tech-savvy leadership, a resource rooted in the immediate supervisor's technology-related competence and enabling behavior, is positively associated with workforce engagement, even when transformational and agile leadership are considered. Second, by drawing on work–family enrichment theory, this study links engagement to employees' lives outside work; the association between engagement and work–life balance is consistent with enrichment arguments, although its direction cannot be established with these data. Third, the very small and method-dependent indirect effect through work–life balance may indicate that, in the demanding Bangladeshi IT sector, work–life balance (WLB) plays at most a limited linking role between engagement and workforce mental health. Finally, this study adds evidence from an emerging economy that remains under-represented in research on leadership and workplace mental health.

6.4. Practical implications

The practical implications should be interpreted in light of the modest effect sizes and cross-sectional design. First, because tech-savvy leadership was positively associated with workforce engagement, IT organizations may consider developing

supervisors' technological competence and their ability to guide employees in the use of new technologies, for example, through targeted training for team leaders. Second, behavioral clarity was also associated with engagement, which suggests that the clear communication of instructions, goals, and deadlines is a low-cost practice worth reinforcing. Third, workforce engagement and social support from peers showed the strongest direct associations with workforce mental health; therefore, practices that foster engagement and collaboration among colleagues may be valuable. Finally, because work–life balance showed only a small association with workforce mental health and did not significantly mediate the engagement–mental health relationship, its practical importance should not be overstated. These recommendations are offered as considerations for practice rather than as tested interventions, and their effectiveness should be evaluated in future research.

7. Limitations and future research directions

Several limitations of this study also point to directions for future research. First, the sample was drawn through convenience sampling from the IT sector in Dhaka and highly educated employees. Future studies using probability-based samples across regions and sectors could establish how far the findings generalize.

Second, workforce mental health was measured with a short, perception-based scale capturing its positive, work-related dimension rather than psychological symptoms. Work–life balance and social support from peers were measured with two items each, the negatively worded behavioral clarity item loaded weakly, and the discriminant validity of tech-savvy leadership against digital leadership and e-leadership could not be tested. Although all constructs met the reliability and validity criteria, future research should use validated mental-health instruments and multi-item scales for each construct. In addition, the items measuring workforce engagement and workforce mental health partly capture perceived support and work-related meaning, which limits their content validity; the findings should therefore be interpreted as relating to these specific aspects of engagement and to positive, work-related mental health.

Third, the cross-sectional, single-source design does not permit causal conclusions, and the relationship between workforce engagement and work–life balance may be reciprocal. Statistical tests suggested that common method bias was not a serious concern, but because not all recommended procedural remedies were applied, it cannot be fully ruled out. Longitudinal and multi-source designs would strengthen causal inference.

Finally, the study examined only the motivational pathway of the JD-R model, which provides a focused view of how job resources relate to engagement and mental health.

Future research could model job demands, such as workload and digital fatigue, to test the full JD-R model and the buffering role of the resources examined here.

8. Conclusion

This study examined the relationship between tech-savvy leadership, behavioral clarity, workforce engagement, and workforce mental health among 419 IT professionals in Bangladesh, along with the roles of work–life balance and social support from peers. Tech-savvy leadership and behavioral clarity were positively associated with workforce engagement, and workforce engagement, work–life balance, and social support from peers were positively associated with workforce mental health. However, work–life balance did not significantly mediate the engagement–mental health relationship under the pre-specified t-test criterion; because the percentile bootstrap confidence interval narrowly excluded zero, this conclusion depends on the method used. The associations were modest, and the cross-sectional, single-source design did not permit causal conclusions. Nevertheless, the findings suggest that supervisors' technological competence, clear

expectations, workforce engagement, and supportive peer relationships are relevant workplace resources for IT professionals' positive, work-related mental health at work, and they provide a basis for longitudinal and multi-source research in emerging economies in the future.

Author contributions: SAP conceptualized and supervised the research, developed the methodology, conducted the data analysis, and critically reviewed and edited the original manuscript. MMR contributed to the conceptualization and structural development of the research, collected and organized the data, and drafted the initial manuscript. ISW contributed to the literature review, supported data analysis and interpretation, prepared figures and tables, and participated in manuscript review and revision.

Competing Interests: The authors declare no competing interests.

Acknowledgments: The authors acknowledge all individuals and institutions who provided support and assistance during the course of this research. The authors are grateful for the encouragement, technical support, and resources that contributed to the successful completion of this study. The authors also acknowledge the valuable feedback and assistance received during the research.

Ethical statement: The study was conducted in accordance with the Declaration of Helsinki, and ethically approved by the Institutional Review Board of Bangladesh Institute of Governance and Management prior to the commencement of the research. The study was approved by the Institutional Review Board of the Bangladesh Institute of Governance and Management in December 2024, prior to the commencement of data collection. No reference number was issued for this approval. The approval covered all stages of data collection, including the pilot study conducted from January to mid-February 2025, whose responses were included in the final analysis.

Informed Consent: All participants provided informed consent electronically after being briefed on the study's purpose, procedures, risks, and withdrawal rights. Participation was voluntary, and no names, email addresses, or other identifying information were collected. Participant data were anonymized to maintain confidentiality and privacy of the participants.

Data availability: Data may be available upon reasonable requests.

Funding Declaration: The authors received no funding for this study.

Use of AI Tools: During the revision of this manuscript, the authors used an AI-based assistant (Claude, ChatGPT) to support language editing, consistency checking of terminology and references, and drafting of the revised text and response to reviewers. All AI-assisted content was reviewed, verified, and edited by the authors, who took full responsibility for the accuracy and integrity of the manuscript. The AI tool was not used to generate or analyze the data and was not listed as an author.

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Supplementary Table 1: Item-level mapping for workforce engagement and workforce mental health

Code	Item (as administered)	Original item	Source / conceptual basis	Adaptation
OPN1	I feel supported and empowered to contribute meaningfully to my organization's goals.	None (author-developed)	Graen & Uhl-Bien (1995)	New item; support and empowerment
OPN2	I feel valued and motivated to share my ideas and perspectives at the workplace.	None (author-developed)	Graen & Uhl-Bien (1995)	New item; voice and feeling valued
OPN3	I feel a strong sense of connection and belonging to my team.	None (author-developed)	Graen & Uhl-Bien (1995)	New item; belonging
JSATIS1	I feel psychologically supported and can maintain my mental well-being at work.	None (author-developed)	World Health Organization (2022)	New item; psychological well-being at work
JSATIS2	My work provides me with a sense of purpose and accomplishment without negatively affecting my mental health.	None (author-developed)	World Health Organization (2022); Judge et al. (2001)	New item; purpose and accomplishment
JSATIS3	My organization creates an environment in which employees' mental health and well-being are valued and supported.	None (author-developed)	World Health Organization (2022)	New item; organizational support for mental health

Note. All six items were developed by the authors for this study, informed by the cited works, reviewed by academic and industry experts, and pilot-tested with IT professionals before the main survey. Items were rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Workforce engagement reflects the participative aspects of engagement (support, voice, and belonging) rather than vigor, dedication, and absorption; workforce mental health reflects positive, work-related mental health rather than clinical symptoms.

Supplementary Table 2: Bootstrap results for specific indirect effects

Indirect path	O	M	SD	t	p	Percentile 95% CI	Bias-corrected 95% CI
Workforce engagement → Work–life balance → Workforce mental health (H6)	0.014	0.014	0.009	1.558	0.119	[0.001, 0.035]	[0.002, 0.037]
Tech-savvy leadership → Workforce engagement → Workforce mental health	0.057	0.057	0.022	2.559	0.011	[0.019, 0.104]	[0.020, 0.106]
Behavioral clarity → Workforce engagement → Workforce mental health	0.027	0.029	0.013	2.117	0.034	[0.008, 0.057]	[0.007, 0.056]
Tech-savvy leadership → Workforce engagement → Work–life balance	0.041	0.042	0.019	2.169	0.030	[0.010, 0.083]	[0.011, 0.084]
Behavioral clarity → Workforce engagement → Work–life balance	0.020	0.021	0.011	1.796	0.073	[0.004, 0.046]	[0.004, 0.044]
Tech-savvy leadership → Workforce engagement → Work–life balance → Workforce mental health	0.004	0.004	0.003	1.428	0.153	[0.000, 0.012]	[0.001, 0.013]
Behavioral clarity → Workforce engagement → Work–life balance → Workforce mental health	0.002	0.002	0.002	1.221	0.222	[0.000, 0.006]	[0.000, 0.007]

Note. Results from SmartPLS 4 bootstrapping (5,000 subsamples, two-tailed). O = original sample estimate; M = bootstrap sample mean; SD = bootstrap standard deviation. Only H6 was hypothesized; the remaining indirect effects are reported for completeness. Values are rounded to three decimals. Construct labels follow the manuscript.

Supplementary Table 3: Summary of supplementary analyses

No.	Analysis	Procedure	Result	Conclusion
1	Alternative leadership styles	Transformational and agile leadership added as predictors of workforce engagement	Tech-savvy leadership remained significant ($\beta = 0.295$, 95% CI [0.179, 0.405]); transformational ($\beta = 0.060$) and agile leadership ($\beta = 0.039$) were not significant	Tech-savvy leadership is empirically distinct
2	Uniform response patterns	Exclusion of two respondents with identical scores on all 59 items, then of a third with identical scores on the 16 study items	All direct paths remained significant; work–life balance → workforce mental health was the weakest path ($\beta = 0.096$, $p = .042$) after the third exclusion; H6 indirect effect = 0.011 ($t = 1.403$, $p = .161$; 95% CI [0.0001, 0.031])	Least robust result; interpret with caution
3	Demographic control variables	Age, gender, education, and work experience added as controls	Path coefficients changed by at most 0.004; no control variable was significant	Results not attributable to demographic differences
4	Reverse direction	Alternative model with work–life balance → workforce engagement	Significant path ($\beta = 0.102$, 95% CI [0.017, 0.188]); $\Delta BIC < 2$ between models	Relationship may be reciprocal
5	Endogeneity	Gaussian copula approach (Hult et al., 2018)	Possible endogeneity only for tech-savvy leadership → workforce engagement; path remained positive and significant	Main result holds
6	Multigroup analysis	Gender, job level, and work experience; measurement invariance assessed with MICOM	Full measurement invariance; no group differences remained significant after Bonferroni correction	Results consistent across groups
7	Statistical power	Inverse square root method (Kock & Hadaya, 2018)	$n = 419$ sufficient for all paths except the smallest ($\beta = 0.104$; required $n = 571$)	Interpret the smallest path with caution

Note. All analyses were estimated in SmartPLS 4 with bootstrapping (5,000 subsamples). See Section 5.9 for details.