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A HUMAN-CENTERED APPROACH TO REFRAMING JOB SATISFACTION IN THE BIM-ENABLED CONSTRUCTION INDUSTRY

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Sharareh Mirzaei, Ph.D Candidate
Gerald May Dept. of Civil, Construction and Environmental Engineering, University of New Mexico
https://orcid.org/0009-0004-7709-4401
shmirzaei@unm.edu

Stephanie Bunt, Assistant Professor
School of Architecture and Planning, University of New Mexico
https://orcid.org/0000-0001-6658-8802
sbunt@unm.edu

Susan M Bogus, Professor
Gerald May Dept. of Civil, Construction and Environmental Engineering, University of New Mexico
https://orcid.org/0000-0003-1685-6367
sbogus@unm.edu

SUMMARY: *As the construction industry undergoes rapid digital transformation, ensuring that new technologies enhance rather than hinder human experience has become essential. Building Information Modeling (BIM) plays a central role in this shift, yet its influence on job satisfaction remains underexplored. In response, this study developed a human-centered measurement model for evaluating job satisfaction in BIM-enabled work environments by adapting Hackman and Oldham's Job Characteristics Model (JCM) for the architecture, engineering, and construction (AEC) industry to create a survey that captured industry perspectives on BIM use and job satisfaction. The model uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the survey results and identify which dimensions of BIM-related work affect job satisfaction. While it was hypothesized that BIM use increases job satisfaction, the results show that only some dimensions of BIM use positively impact BIM job satisfaction; the use of BIM alone does not guarantee an increase in overall job satisfaction. Additionally, more frequent BIM use was not directly associated with Overall-JS; however, it was positively associated with BIM-JS and had an indirect effect on Overall-JS through BIM-JS. These findings suggest that in the BIM-enabled workplace, Sustainable job satisfaction in BIM-enabled workplaces depends less on technological autonomy and more on collaboration, meaningful engagement, constructive feedback, and the reduction of workflow pain points.*

KEYWORDS: *Building Information Modeling (BIM), job satisfaction, technology adoption, architecture, engineering, and construction (AEC) industry, human factors.*

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1. INTRODUCTION

Building Information Modeling (BIM) is a transformative force in the architecture, engineering, and construction (AEC) industry, driving significant gains in productivity, data accuracy, and project delivery efficiency. By enabling real-time information exchange, reducing communication bottlenecks, automating routine processes, and restructuring coordination practices, BIM reshapes how projects are planned and performed, from early design phases to facility operations and maintenance (Hallén et al., 2023).

Beyond technical efficiency, BIM adoption fundamentally reshapes work organization, professional roles, and interpersonal collaboration in the AEC industry. Research shows that adopting BIM is not merely a technological upgrade but a transformation in organizational practices and culture that redefines traditional stakeholder roles and relationships and promotes shared interaction within a common digital project environment (Chen et al., 2024). Such restructuring alters established workflows and communication patterns that are closely linked to employees' psychological experience of work and their ability to navigate organizational change (Huang et al., 2022).

However, these workflow transformations do not uniformly enhance well-being. Empirical evidence indicates that BIM implementation can also introduce new stressors, including increased job stress among design-office professionals, with stress levels varying by career stage, gender, training exposure, and the availability of standardized BIM templates (Hua & Zhang, 2024). In some contexts, enforced or highly routinized BIM use has been associated with role tension, reduced creative autonomy, and professional distress, particularly when rigid digital procedures conflict with designers' creative identities (Hermund, 2009). Collectively, this body of evidence indicates that BIM can generate measurable shifts in job satisfaction and psychological well-being, highlighting the need for systematic investigation of its human-centered impacts.

Understanding how digital systems reshape workers' engagement is crucial not only for sustaining productivity gains but also for maintaining job satisfaction in technologically mediated environments (Bolli & Pusterla, 2022). Given the AEC industry's reliance on human labor (Dainty et al., 2007) and its long-standing issues with job dissatisfaction (CDC, 2021; Holistic Healthcare Group, 2020; Tijani et al., 2021), studying job satisfaction has become increasingly important, especially as emerging digital technologies introduce new complexities and demands into the workplace.

Accordingly, this study shifts attention toward the human impact of BIM by developing a framework for understanding job satisfaction in digitally mediated AEC workplaces. Digital adoption should not be viewed as a one-time event, but rather as an ongoing transformation in how work is organized and performed. Continuous post-adoption evaluation is essential to ensure that both the technical and human dimensions of change are addressed (Greenhalgh et al., 2017).

This study addresses a gap in current research by examining job satisfaction (JS) within BIM-enabled AEC work environments through the development of a novel BIM Job Satisfaction (BIM-JS) Measurement Model. The model conceptualizes BIM-JS by building on Hackman and Oldham's Job Characteristics Model (JCM) and incorporating additional factors. The JCM was selected because it explicitly links work design characteristics to psychological states and job satisfaction outcomes. Although some theoretical frameworks, such as socio-technical systems theory, provide a valuable macro-level perspective on how digital technologies reshape organizational structures and work systems (Bostrom & Heinen, 1977; Trist, 1981), they do not offer specific, operationalized mechanisms for examining individual-level job satisfaction outcomes. Similarly, the Job Demands–Resource model primarily focuses on employee strain, burnout, and engagement through the balance of job demands and resources (Demerouti et al., 2001; Bakker & Demerouti, 2007). In contrast, the present study seeks to examine how BIM restructures core task characteristics and how these structural changes influence employees' psychological experience of work. This makes the JCM theoretically well aligned with the study's objective of evaluating BIM's impact on job satisfaction through work design mechanisms in post-adoption contexts.

The model includes three selected JCM dimensions. The first is experienced meaningfulness, defined as the extent to which BIM-enabled work supports skill variety, task identity, and task significance (Hackman, 1974). The second is feedback, referring to the extent to which BIM enables clear and timely performance evaluation (Hackman, 1974). The third is autonomy, which refers to the degree to which professionals can make independent decisions when using BIM tools. While the JCM provides a strong foundation for analyzing job satisfaction, its original formulation does not fully reflect the realities of digital work environments. To address this gap, the proposed BIM-JS Measurement Model builds on three selected JCM dimensions by introducing two additional factors: collaboration, a strong predictor of job satisfaction in digital contexts (Wong et al., 2014), and pain-point improvement, which captures the social and experiential aspects of BIM-enabled work. Collaboration reflects the quality of interdisciplinary engagement fostered by BIM, while pain-point improvement represents the role of technology in alleviating long-standing inefficiencies common in AEC projects. Together with meaningfulness, autonomy, and feedback, these factors form a human-centered framework for evaluating job satisfaction in digital construction settings.

The BIM-JS Measurement Model is used to examine the first research question (RQ1), which asks which of the JS factors (meaningfulness, collaboration, autonomy, feedback, and pain-point improvement) significantly and positively contribute to the formation of the BIM Job Satisfaction construct? The second research question (RQ2) asks whether BIM-related job satisfaction can be used to predict overall job satisfaction. After creating the BIM-JS Measurement Model, the structural relationship between BIM-JS and Overall-JS can be assessed. Although BIM may improve JS, we recognize that not all professionals use BIM to the same extent, leading to the third research question (RQ3), which asks whether the frequency of BIM use influences BIM-JS or Overall-JS. To address these questions, hypotheses about the JS factors were evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM), and a Confirmatory Composite Analysis was used to validate the structure, reliability, and appropriateness of composite constructs in the BIM-JS Measurement Model, ensuring that the indicators and their relationships to constructs are theoretically and statistically justifiable. By centering human experience, this study offers a novel perspective on BIM-JS in the AEC industry.

2. LITERATURE REVIEW

2.1 BIM definitions and benefits

BIM has emerged as a transformative digital innovation in the AEC industry, offering a collaborative and integrated approach to managing the lifecycle of built assets. Although definitions vary by context, BIM is broadly recognized as a 3D model-based methodology for planning, designing, constructing, and operating infrastructure (Muta et al., 2025). It also functions as a comprehensive system for managing design and project data (Volk et al., 2014), and as a collaborative framework that integrates technological, managerial, and human factors to enhance project execution and facility management (Oraee et al., 2017).

At its core, BIM consolidates multidisciplinary data within a unified digital environment, improving accuracy, reducing errors, and increasing transparency throughout the project lifecycle (Hallén et al., 2023). Its growing adoption reflects broader digitalization trends across the construction sector, with documented improvements in productivity, decision-making, and operational efficiency (Azhar, 2011). Through synchronized, real-time information exchange, BIM enhances process efficiency, fosters stakeholder accountability, and strengthens team motivation (Lee et al., 2023). Cloud-based BIM platforms further support coordination, with studies showing significant improvements in project outcomes. When paired with structured change management and ongoing training, organizations report productivity gains ranging from 70% to 240% (Oakland & Tanner, 2007; Poirier et al., 2015).

The human-centered benefits of BIM are particularly evident in its capacity to streamline collaboration among stakeholders (Villena Manzanares et al., 2024). Its digital environment supports iterative updates and centralized feedback, facilitating effective coordination across disciplines, including engineers, supervisors, and contractors (Azhar, 2011; Guo et al., 2019). One of the most impactful features of BIM is its advanced visualization capability; interactive 3D models help both technical and non-technical users understand design intent, enabling earlier feedback, higher design quality, and reduced rework (Chu et al., 2018). Beyond coordination, BIM also supports performance simulation, allowing teams to model outcomes such as energy efficiency and structural behavior, which helps anticipate risks and improves confidence in cost, scheduling, and feasibility assessments (Villena Manzanares et al., 2024).

Technologically, BIM provides a foundation for automation and real-time data exchange. Its cloud-based architecture ensures continuous access to up-to-date project data, supporting more agile and responsive management. Furthermore, BIM's compatibility with emerging technologies, such as digital twins and the Internet of Things (IoT), enhances its value by enabling predictive maintenance, optimizing building performance, and supporting intelligent facility management (Love et al., 2014).

However, despite the considerable promise of BIM's technical capabilities, their effective realization in practice remains uneven. Implementation efforts are often impeded not solely by technical limitations but by a broader set of challenges. Organizational inertia, workflow disruptions, and resistance to change among stakeholders continue to present substantial barriers to successful integration. The following section explores these constraints in depth, examining the technological, human, and institutional factors that influence the adoption and effective use of BIM across the AEC industry.

2.2 BIM user resistance

Human-related challenges remain among the most persistent and underexamined influences in BIM implementation. In the AEC industry, successful technological transitions depend not only on system capabilities but also on user readiness and organizational support. Technology adoption is often portrayed as a static decision by an individual or organization to embrace an innovation. However, a growing body of research suggests that it is better understood as a dynamic, iterative, and multi-stage process that evolves over time, operates across multiple organizational levels, and involves continuous cycles of evaluation, adjustment, and renewed commitment (Greenhalgh et al., 2017; Mambile et al., 2024). Accordingly, many conditions that emerge during initial implementation persist into the post-adoption phase and continue to reshape employees' work experience.

BIM alters workflows, redefines responsibilities, and demands new competencies. These structural changes extend beyond technical system usage and reshape how tasks are coordinated, how roles are distributed, and how collaboration unfolds across project teams (Arayici et al., 2011; Poirier et al., 2017; Suprun et al., 2019). From a sociotechnical systems perspective, technological change reshapes both the technical and social dimensions of work, altering task structures, coordination mechanisms, and role relationships in ways that influence employees' psychological experience and job satisfaction (Venkatachalam et al., 2023; Okolo et al., 2019). As a result, the psychological experience of work, rather than merely system usage, becomes central to evaluating implementation outcomes.

Resistance to change remains one of the most documented human responses to such transformation. Behavioral inertia limited organizational support, and concerns about productivity disruption can hinder adjustment to new digital workflows (Evans & Britt, 2023). Psychological barriers, including uncertainty toward new technologies and attachment to legacy systems such as CAD, further complicate adaptation (Klein et al., 2022). When BIM is perceived as imposed without meaningful participation, skepticism and disengagement may extend beyond implementation and influence how employees evaluate their evolving roles within digitally transformed environments (Arayici et al., 2011). Importantly, these challenges are not confined to the moment of adoption.

Many professionals weigh the cognitive effort of learning new tools against the perceived loss of competence or investment in familiar systems. Addressing these tensions requires more than technical solutions. Effective change management, including leadership commitment, transparent communication, and user involvement, is essential for successful BIM implementation. Where such support is limited, altered role expectations and increased coordination demands may contribute to dissatisfaction, even when BIM systems are technically operational.

Despite growing recognition of these human dimensions, most existing studies emphasize pre-adoption barriers and successful implementation. Far less attention has been given to how ongoing changes in roles, responsibilities, and coordination patterns influence job satisfaction in the post-adoption phase. Understanding BIM through this post-adoption lens is, therefore, essential for evaluating its long-term impact on workforce well-being in the AEC industry.

2.3 Job satisfaction & measurements

Job satisfaction is one of the most widely studied topics in organizational research. It reflects how employees feel and think about their work. Traditionally, job satisfaction has been defined as a positive emotional state that results from evaluating one's job or work experiences (Sonnenfeld, 1985). It includes how people respond to their tasks, work environment, and how well their job aligns with personal goals. Earlier research focused on external factors like pay, job security, and working conditions. However, more recent studies emphasize internal factors such as autonomy, purpose, opportunities for growth, and meaningful work (Ćulibrk et al., 2018; Sang et al., 2009). These intrinsic elements are especially important in modern, knowledge-based jobs where people value personal development and impact. Job satisfaction has been linked to many positive outcomes, including higher

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productivity, lower turnover, stronger commitment, and greater innovation (Somvir & Kaushik, 2012; Villena Manzanares et al., 2024).

2.4 Job characteristics model

To systematically understand how job characteristics influence satisfaction and motivation, Hackman and Oldham developed the JCM in the 1970s, a framework that remains widely applied in contemporary job design research. The model identifies five core job factors: skill variety, task identity, task significance, autonomy, and feedback. Each of these contributes to three critical psychological states: experienced meaningfulness of work, responsibility for outcomes, and knowledge of results of activity (J. Hackman, 1974; J. R. Hackman, 1980). When these psychological states are activated, employees are more likely to experience intrinsic motivation and higher job satisfaction.

The feeling that one's job is meaningful arises when individuals perceive their tasks as significant and valuable (Hackman, 1974). This sense of meaningfulness is commonly shaped by three core job characteristics: skill variety, task identity, and task significance. Skill variety refers to the presence of diverse work activities and the opportunity to apply a range of skills to accomplish tasks. Task identity is defined as the ability to complete an entire and clearly identifiable piece of work. Task significance reflects the perceived impact of one's job on others and its contribution to organizational success (Hackman, 1974). When these elements are present, employees are more likely to find their work engaging and personally fulfilling. In the context of BIM, job satisfaction may be enhanced by increasing employees' sense of meaningfulness in their work. This leads to the first hypothesis:

- H1a: Meaningfulness positively and significantly predicts BIM-JS.

Beyond a sense of meaningfulness, JCM measures feedback and autonomy through the process. Feedback relates to the clarity and immediacy of information employees receive about their job performance. When workers can observe the results of their efforts through direct task-related cues, it helps them evaluate their effectiveness, make necessary improvements, and enhance confidence (Belletier et al., 2021). Autonomy, on the other hand, refers to the degree of independence an employee has in making decisions on their work and feels responsible for the outcome. Jobs that offer high autonomy tend to foster a stronger sense of accountability, as individuals feel their input directly affects outcomes (Hackman, 1974). These factors play a crucial role in creating motivating work environments that support job satisfaction and performance (Hackman, 1974). Therefore, this study examines these factors of job satisfaction through the following hypotheses:

- H1b: Feedback positively and significantly predicts BIM-JS.
- H1c: Autonomy positively and significantly predicts BIM-JS.

Numerous studies have validated the JCM's utility in various sectors, including manufacturing, healthcare, education, and construction. For instance, in environments where task repetition and hierarchical control dominate, JCM helps to redesign tasks to improve worker engagement by increasing autonomy and clarifying the importance of tasks (Sun et al., 2022). In technology-supported roles, the JCM has been applied to evaluate levels of job satisfaction. Real-time feedback tools, such as wearable devices and performance dashboards, align well with the model's feedback dimension, enhancing workers' responsiveness and confidence (Belletier et al., 2021). Recent research has further used or extended JCM to examine emerging technologies such as Artificial Intelligence (AI). These extensions suggest that AI-enabled job features (e.g., autonomy, skill variety, information processing, and complexity) influence outcomes such as innovative work behavior and technology acceptance (Chen et al., 2023; Verma & Singh, 2022; Younis et al., 2024).

Additionally, JCM has been used to evaluate job design in knowledge-intensive industries, where the complexity of tasks and autonomy in problem-solving are key contributors to satisfaction. These findings demonstrate that JCM remains a relevant and flexible model for studying workplace motivation and satisfaction, particularly in environments that seek to balance structure and innovation.

However, as workplaces become more digitized and reliant on information systems, scholars have begun to question whether the JCM adequately captures the dynamics of technology-mediated work. In particular, digital tools like BIM, Enterprise Resource Planning (ERP) systems and AI platforms introduce new forms of task interaction, decision-making, and feedback that differ substantially from the work environments originally described in the JCM. For example, Morris and Venkatesh (2010) found that the JCM's five core factors explained only 47% of the variance in job satisfaction among ERP system users, suggesting the presence of other unaccounted-for variables such as system usability, interface quality, and user trust. These findings highlight the limitations of relying solely on traditional job design frameworks when assessing job satisfaction in digitally transformed workplaces. Accordingly, this study extends the JCM to capture job satisfaction factors specific to BIM-enabled work environments in the AEC industry. Recent critiques suggest that conventional job satisfaction models often overlook the role of digital systems in shaping contemporary work experiences and should therefore be expanded to include domain-specific factors that influence job satisfaction (Murphy et al., 2012). Despite being somewhat dated, the JCM remains among the most widely cited models in this field, focusing on how specific job features impact motivation and satisfaction through various psychological mechanisms.

2.5 Beyond JCM

While the JCM provides a foundational framework for analyzing job satisfaction across a wide range of roles and industries (Hackman & Oldham, 1976), many scholars have argued that its generality limits its ability to fully capture the complexity of contemporary work environments. As work becomes increasingly digitized, project-based, and interdependent, the structural conditions that shape employees' psychological experiences extend beyond traditional task characteristics and are increasingly transformed by technology. Consequently, numerous studies have extended or adapted the JCM to better align with specific domains or technological contexts. More recent research in high-tech and project-based settings highlights additional domain-sensitive factors, including system usability, technological dynamism, and interdisciplinary collaboration (Morgeson et al., 2006; Bayo-Moriones et al., 2010). These extensions do not replace the psychological mechanisms proposed by the JCM but rather refine the structural antecedents that generate those mechanisms.

The JCM posits that job satisfaction arises from core work design features that shape employees' psychological states (Hackman & Oldham, 1976). In digitally mediated environments, technology does not merely support existing tasks but can fundamentally restructure how work is coordinated, executed, and evaluated (Bostrom & Heinen, 1977; Trist, 1981). Within BIM-enabled construction contexts, shared digital models, real-time coordination mechanisms, and integrated information platforms increase interdisciplinary task interdependence and collective accountability (Succar, 2009; Eastman et al., 2011). Collaboration is widely recognized as a defining structural feature of BIM rather than a secondary benefit. For instance, Raza et al. (2023) identify collaboration and communication as primary BIM characteristics, noting that access to a unified digital model enables effective teamwork across construction projects.

At the same time, BIM is explicitly designed to reduce persistent workflow inefficiencies, such as rework, coordination conflicts, and information fragmentation, that have historically characterized AEC practice (Azhar, 2011; Bryde et al., 2013). By improving information transparency, clash detection, and process integration, BIM stabilizes task execution and enhances feedback clarity, thereby altering daily work conditions. The reduction of such "pain points" reflects tangible improvements in work design rather than subjective technology appraisal.

Unlike adoption-oriented constructs such as perceived usefulness, which primarily explain technology acceptance and usage intention (Davis, 1989), collaboration and pain-point relief capture structural transformations in post-adoption work experience. As such, they constitute theoretically grounded, domain-sensitive extensions of the JCM within BIM-enabled environments.

2.5.1 Collaboration

A review of domain-specific literature reveals that collaboration frequently emerges as one of the most critical factors used to measure job satisfaction, particularly in digitally intensive and project-based environments such as AEC. Across numerous studies, collaboration is a critical driver of job satisfaction, as it fosters shared responsibility, mutual support, and a sense of collective achievement (Pedrycz et al., 2011). Workplace dynamics shaped by effective teamwork can significantly influence how individuals perceive their roles and overall satisfaction (Locke, 1969). This is a complex issue, particularly in the modern workplace, where individual job satisfaction is closely linked to both team performance and overall team satisfaction (Pedrycz et al., 2011). In 1984, Goldstein and Rockart extended the JCM by introducing variables that account for relationships among coworkers. Their research highlighted that collaborative work significantly moderates the link between job characteristics and job satisfaction. For example, the satisfaction derived from a task can vary depending on whether it is performed individually or within a collaborative context (Wong et al., 2014). Collaboration and information exchange remain persistent challenges in the construction industry. These challenges largely stem from the fragmented and decentralized nature of data management within the sector (Saka & Chan, 2021). In this context, cloud-based BIM presents a transformative and collaborative environment by offering a centralized digital platform that promotes seamless communication and coordinated project workflows (Wong et al., 2014; Souza et al., 2023). Given the emphasis on collaboration as a key factor in job satisfaction and the importance of that in AEC, we extend the existing model with the following hypothesis:

- H1d: Collaboration positively and significantly predicts BIM-JS.

To define the final key factor contributing to job satisfaction in the AEC industry, it is essential to study how BIM affects long-lasting dissatisfaction. Despite sustained efforts to boost productivity, improve project outcomes, and enhance team collaboration, widespread dissatisfaction persists. These issues endure even in the face of advancing technologies, indicating that digital tools are insufficient unless they address the deeper causes of dissatisfaction. Accordingly, the following section critically explores the dissatisfaction that has long shaped the AEC work environment. Understanding these persistent frustrations is essential to assessing whether, and to what extent, BIM may alleviate them and thereby contribute to improved job satisfaction among construction professionals.

2.5.2 AEC persistent pain points

Despite growing awareness, mental health concerns remain substantial among construction workers in the United States. CPWR reported that 15.4% of construction workers experienced anxiety or depression in 2021, while 30.7% reported feeling anxious at least monthly (Brooks et al., 2024). These figures underscore an urgent need for professional interventions to improve well-being in the AEC sector. The industry's fragmented structure, project-specific workflows, labor-intensive operations, high-risk business environment, and resistance to automation all contribute to these conditions (Hu & Panthi, 2018). Compounding these issues is the entrenched culture of extended work hours, which erodes work-life balance and heightens occupational stress (Hu & Panthi, 2018). Such conditions are strongly linked to lower job satisfaction, diminished organizational commitment, higher turnover, and reduced productivity (Cheung et al., 2022). Additionally, AEC projects are often awarded on short notice in highly competitive environments, requiring the rapid formation of project teams. This volatility forces firms to manage fluctuating workloads without stable work volume assurance (Dainty & Loosemore, 2013), resulting in irregular schedules, tight deadlines, and elevated stress levels (Zheng & Wu, 2018). The industry's cyclical downturns and persistent uncertainty further intensify these pressures, as staffing reductions shift greater responsibility onto fewer workers (Hu & Panthi, 2018).

Also, on the individual level, AEC workers experience elevated job expectations, limited task autonomy, and inadequate social support (Woje et al., 2023). These psychological stressors contribute to a range of negative outcomes, including increased absenteeism, high turnover, lower work quality, and diminished productivity, all of which increase costs and delay project completion (Woje et al., 2023). The Health and Safety Executive (HSE) attributes 80–90% of industrial accidents to personal issues and unmanaged stress (Jansen, 1986), while the European Agency for Safety and Health at Work estimates that stress causes roughly 50% of job-related absenteeism (Simmons & Simmons, 1997).

To assess the extent to which BIM has helped alleviate persistent pain points and contributed to job satisfaction, the following final hypothesis was formulated to complete the response to Research Question 1:

- H1e – Pain points relief positively and significantly predicts BIM-JS.

2.6. From BIM-JS to overall-JS: Direct and mediated effects

Having identified the key BIM work factors, meaningfulness, autonomy, feedback, collaboration, and pain points, that shape the BIM-JS construct, the next step is to examine whether BIM-JS explains incremental variance in Overall-JS (a global evaluation shaped by many non-BIM factors). This analysis helps determine the extent to which BIM-related work conditions contribute to overall satisfaction relative to other established predictors of Overall-JS. To address this question, the following hypothesis is proposed:

- H2: BIM-JS positively and significantly predicts Overall-JS.

In addition to examining the direct relationship between BIM-JS and Overall-JS, this study investigates whether frequency of BIM use influences BIM-JS and Overall-JS, and whether it has an indirect effect on Overall-JS through BIM-JS. Specifically, it explores whether the extent of professionals' engagement with BIM tools influences job satisfaction outcomes. To assess this potential mediation effect, the following hypotheses are proposed:

- H3a (Mediation Path 1): Frequency of BIM use positively and significantly influences BIM-JS.
- H3b (Mediation Path 2): Frequency of BIM use positively and significantly influences Overall-JS.
- H3c (Indirect Effect): Frequency of BIM use has a positive indirect effect on Overall-JS through BIM-JS.

Combining all hypotheses, Figure 1 illustrates the proposed BIM-JS Measurement Model.

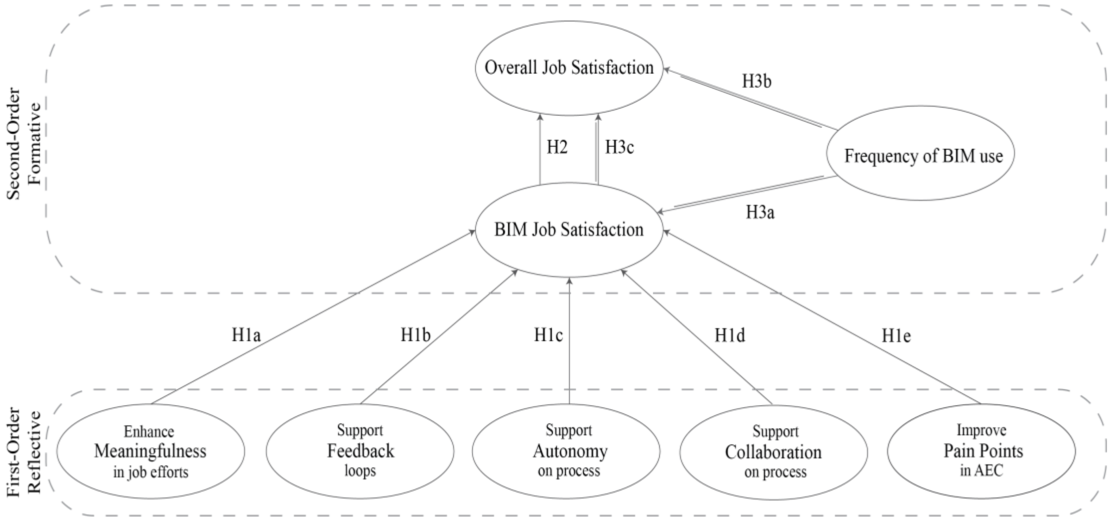

Figure 1: The conceptual BIM-JS Measurement model.

3. METHODOLOGY

Following a comprehensive literature review, developing hypotheses, and the construction of the conceptual measurement model, a survey instrument was designed to collect AEC workers' perspectives on BIM in their workplace. To clearly illustrate the IRB-approved research process, Figure 2 presents the sequential workflow in this study and references the section numbers where each step is developed. The following sections detail the methodology employed in this paper.

3.1 Survey design

This study used a cross-sectional online survey to investigate job satisfaction and BIM use among professionals in the AEC industry. The survey instrument was designed to capture information on participants' demographic characteristics, professional background, level of BIM engagement, as well as overall job satisfaction and BIM-specific job satisfaction, to develop a model to measure BIM-JS.

The BIM-JS Measurement Model combined five JS factors to assess BIM-mediated work dynamics. First, the JCM was adapted to the AEC context, identifying core factors such as meaningfulness, autonomy, and feedback. Collaboration, as the fourth factor, was synthesized from a targeted literature review on technology-enabled work, drawing from both AEC and related domains. Lastly, the framework incorporated AEC-specific pain points reflecting persistent operational frictions that are known to negatively impact job satisfaction. In the survey, each factor included questions designed to capture participants' perceptions of that factor within a BIM-enabled workplace. Each was measured using a specific number of survey items, depending on its scope and complexity. For example, meaningfulness was assessed using seven items (MF1–MF7), reflecting the full range of sub-factors in Hackman and Oldham's JCM (i.e., skill variety, task identity, and task significance). In contrast, factors such as feedback (FB1) and autonomy (Aut1) were measured with single items due to their more narrowly defined operational scope.

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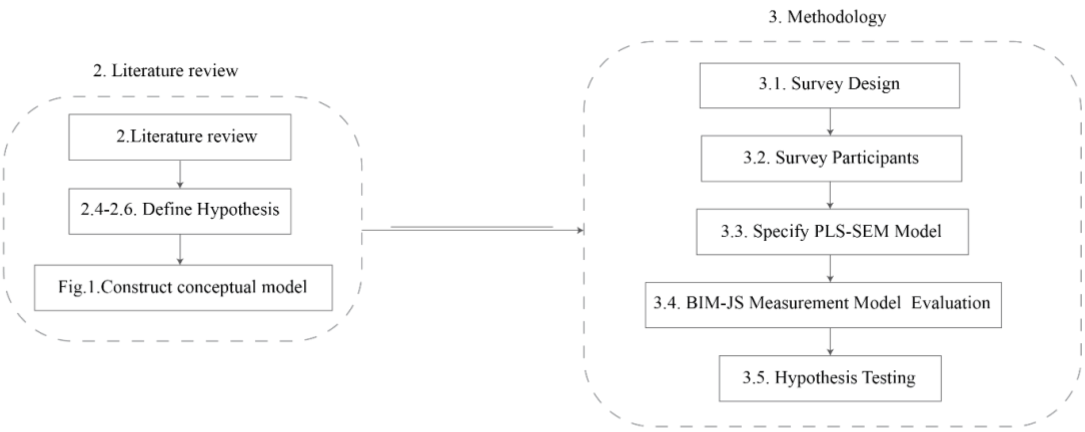

Figure 2: Research workflow.

Together, these components allow for the study of job satisfaction through various dimensions and provide a holistic perspective on BIM-JS. All survey items, except those in the demographic section, employed a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The survey questions used in the data analysis are provided in Table 1.

Table 1: Survey items used in the BIM-JS measurement model.

Code		Question
OJ1	Overall-JS	In general, I enjoy doing my current job.
OJ2	Overall-JS	I understand my responsibilities
OJ3	Overall-JS	I enjoy the people I work with.
OJ4	Overall-JS	My current job aligns with my career goals.
OJ5	Overall-JS	I feel that what I am doing at my job is important.
MF1	Meaningfulness	BIM enables me to engage in diverse project areas beyond my usual tasks.
MF2	Meaningfulness	BIM models and data in coordination meetings help me learn from contractors and apply diverse skills.
MF3	Meaningfulness	BIM makes me feel more responsible for my tasks.
MF4	Meaningfulness	BIM clarifies how my tasks fit into the broader project and the result.
MF5	Meaningfulness	BIM models and data help me feel that my work benefits the team.
MF6	Meaningfulness	BIM models and data help me see my work's contribution to client value.
MF7	Meaningfulness	BIM models and data help me see how my work supports larger goals, such as sustainability
Aut1	Autonomy	BIM provides the information and tools needed to make independent task decisions.
FB1	Feedback	BIM enables quick and constructive feedback from supervisors and team members.
Col1	Collaboration	BIM models and data enhance internal team collaboration, such as sharing updates or solving issues together.
Col2	Collaboration	BIM fosters collaboration across different teams, such as design, engineering, and construction.
Col3	Collaboration	BIM improves communication and coordination between on-site and off-site teams.
Col4	Collaboration	BIM makes my workflow easier and more organized.
PS1	Pain point	BIM reduces manual drafting and simplifies design visualization.
PS2	Pain point	BIM reduces the stress of tight deadlines by streamlining processes.
PS3	Pain point	BIM models and data reduce mental stress by improving clarity and communication, and by reducing rework.
PS4	Pain point	Using BIM has saved me time.

OJ = Overall Job Satisfaction, MF = Meaningfulness, Aut = Autonomy, FB = Feedback, Col = Collaboration, PS= Pain-point Improvement

3.2 Survey participants

After designing the survey, a pilot study was conducted with five professionals to evaluate the draft survey before full deployment. The pilot group included two project managers, two BIM specialists, and one architectural professional selected from a glazing company and a design-build company. The purpose of the pilot was to assess item clarity, wording, relevance to BIM-enabled work conditions, survey flow, and completion time. Participants were asked to identify unclear, ambiguous, or repetitive items and to comment on whether the questions reflected real BIM-related work experiences. The researcher was present while participants completed the pilot survey to observe interpretation difficulties. Based on pilot feedback and observations, the survey was revised by improving wording clarity, refining item phrasing, and adjusting the structure and sequence of questions to improve readability and alignment with industry practice. Pilot responses were used only for instrument refinement and were not included in the final analysis. Survey recruitment for the full study took place between May 2025 and August 2025 through LinkedIn, Autodesk forums, and Autodesk user groups, with a focus on individuals actively involved in BIM-enabled work. A total of 119 responses were collected. The data were screened for missing values, scale validity, and response quality. Following this screening and cleaning process, 86 responses were retained for analysis. The survey collected information about the gender, age, education level, BIM experience, professional roles, BIM usage in projects, and which BIM software they use most regularly. This study used purposive recruitment in BIM-enabled AEC organizations because the research objective focuses on post-adoption job satisfaction in BIM-related work contexts. To ensure that respondents could meaningfully evaluate BIM-enabled work conditions, participants were required to have professional BIM experience. However, the sample was not restricted to high-intensity BIM users; respondents reported a range of BIM-use levels across projects, including low-use categories. Accordingly, the study reflects variation within BIM-enabled contexts rather than the broader AEC workforce, including non-BIM or pre-adoption settings. A summary of the descriptive characteristics of the respondents is shown in Table 2.

Table 2: Descriptive data of participants.

BIM Usage in Projects Category	**Count**	**Percentage**
Sample Size	86	100%
Gender Distribution		
Male	58	67.4
Female	28	32.6
Age Groups		
Under 25	7	8.1
25-34	38	44.2
35-44	25	29.1
45-54	13	15.1
55+	3	3.5
Education Levels		
Under a bachelor’s degree	11	12.8
Bachelor’s degree	33	38.4
Above master’s degree	42	48.8
Work Experience		
Less than 1 year	0	0
1-3 years	15	17.4
4-6 years	21	24.4
7-10 years	16	18.6
10+ years	34	39.5

BIM Usage in Projects Category	Count	Percentage
BIM Experience		
Less than 1 year	7	8.1
1-3 years	15	17.4
4-6 years	21	24.4
7-10 years	19	22.1
10+ years	24	27.9
Professional Roles		
Architect	25	29.1
Engineer	20	23.3
Project Manager	9	10.5
BIM Specialist	23	26.7
Contractor	5	5.8
Other Roles	4	4.6
BIM Software		
Only Autodesk Revit	40	44
Autodesk Revit + Navisworks	33	36
Other software	13	15
Frequency of BIM Use in Project		
Under 15%	7	8
16-30%	8	9
31-60%	9	10
Above 60%	62	72

3.3 Specify PLS-SEM model

In this step, the conceptual model developed in the literature review was converted into an empirical PLS-SEM model using the Two-Stage Hierarchical Component Modeling approach. First, a conceptual framework was built from prior literature to identify the main factors and formulate testable hypotheses. These hypotheses were then evaluated using PLS-SEM in SmartPLS, with additional diagnostics performed in the statistical analysis program, R. PLS-SEM was chosen because it is well-suited for small sample sizes, non-normal data, and formative constructs, and because the goal of this study is to predict and identify the key drivers of BIM-related job satisfaction (Hair Jr et al., 2021; Henseler et al., 2016). While the PLS-SEM algorithm can involve multiple stages of regression estimation, the two-stage approach was used for this research as it is particularly appropriate for modeling multidimensional, higher-order constructs, like BIM-JS, where several distinct components combine to form the overall concept. Constructs such as satisfaction or happiness do not exist as standalone entities; they are inherently abstract and must be understood through their underlying dimensions or components, which together give the construct its full meaning. In addition, the growing use of this method in recent construction management studies reinforces its suitability for analyzing complex, digitally mediated, and human-centered constructs, further validating its application in this research context (Kineber et al., 2021; Mia et al., 2022; Villena Manzanares et al., 2024).

For this work, the two-stage PLS-SEM algorithm was used. In Stage 1, first-order factors, *meaningfulness*, *collaboration*, and *pain points*, were specified as Mode A (reflective) composites; *autonomy* and *feedback* were single-indicator composites. In Stage 2, first-order latent scores served as formative indicators of the higher-order composite BIM-JS, which then predicted Overall-JS. BIM-JS was modeled as a formative second-order construct because its dimensions (meaningfulness, collaboration, autonomy, feedback, and pain-point improvement) represent distinct and non-interchangeable aspects of BIM-mediated work. Each dimension contributes uniquely to the overall construct, and removing any of them would alter the conceptual meaning of BIM-JS.

3.4 BIM-JS measurement model evaluation

3.4.1 Model evaluation

After specifying the model, it is necessary to assess the quality of measurements to ensure the model's reliability and validity (Henseler et al., 2016). For stage 1 (reflective measurement models), Confirmatory Composite Analysis (CCA) was employed to validate first-order reflective constructs. It involves assessing several key aspects: (1) indicator reliability, (2) internal consistency reliability and convergent validity, and (3) discriminant validity (AlNuaimi et al., 2021).

Indicator reliability was assessed by examining outer loadings, which were expected to exceed the recommended threshold of $\lambda > 0.708$ to confirm that each item of a construct effectively captured its intended construct (Hair Jr et al., 2017). Internal consistency was evaluated using Composite Reliability (CR) to ensure that the items measured the same underlying concept, with CR values above 0.70 indicating acceptable reliability (Nunnally & Bernstein, 1994). Convergent validity was examined using Average Variance Extracted (AVE), where AVE > 0.50 demonstrates that the indicators of each factor share sufficient common variance (Fornell & Larcker, 1981). Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), with HTMT values below HTMT < 0.85 (strict) or < 0.90 (lenient) confirming factors are distinct (Henseler et al., 2015).

Following the CCA analysis in Stage 1, Stage 2 involved evaluating the formative second-order construct. First, multicollinearity was assessed to ensure that the formative indicators provided distinct information and were not excessively correlated, thereby allowing their individual effects on the results to be clearly distinguished. All outer Variance Inflation Factor (VIF) values were below the recommended threshold of 3.3, indicating no critical collinearity issues (Hair Jr, 2021). Next, the outer weights of the first-order dimensions were analyzed to assess their relative contribution to the higher-order BIM–JS composite. Because formative indicators require significance testing, bootstrapping with 5,000 subsamples was applied to evaluate the significance of the outer weights (and outer loadings when needed), using $p < 0.05$ as the criterion. Bootstrapping is essential for formative measurement models because it provides distribution-independent standard errors, ensuring that each dimension contributes meaningfully to the higher-order construct.

3.4.2 Structural model evaluation

After validating the measurement model, the structural model was assessed to evaluate whether the hypothesized relationships are supported and whether the model has explanatory and predictive power (AlNuaimi et al., 2021). Model fit was examined using the Standardized Root Mean Square Residual (SRMR); values below 0.1 indicate that the correlations implied by the model closely match the observed correlations, suggesting an acceptable global fit (Hu & Bentler, 1999). Predictive relevance was evaluated using Stone–Geisser's Q^2 obtained via blindfolding. Q^2 values above zero indicate that the model predicts the endogenous construct better than a baseline approach, with higher values reflecting stronger predictive relevance (Hair Jr et al., 2021). The model's explanatory power for job satisfaction was assessed using R^2, which indicates the proportion of variance explained by its predictors. Finally, Cohen's f^2 was reported to determine the contribution of each predictor to R^2; values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Cohen, 1988).

3.5 Hypothesis testing

For the first research question (H1), path weights from each first-order construct to BIM-JS were examined. This tested whether dimensions such as collaboration, feedback, and autonomy significantly shaped satisfaction with BIM-related work. Loadings and outer weights were used to identify which factors had the strongest influence. The second hypothesis (H2) examined whether BIM-JS, as a higher-order construct, predicted overall job satisfaction. This involved evaluating the direct structural path from BIM-JS to overall-JS. Finally, the third hypothesis (H3) assessed whether the frequency of BIM use influenced overall job satisfaction, and whether this effect was mediated by BIM-JS. The model examined both direct and indirect paths, allowing for the identification of full or partial mediation effects. Together, these procedures enabled a thorough examination of the conceptual model and provided a foundation for interpreting the structural findings presented in the results.

4. RESULTS

This section reports the evaluation of the measurement and structural models of PLS-SEM, following the procedures described in the methodology. The results of hypothesis testing are then presented to assess support for the proposed hypotheses.

4.1 Model evaluation

The measurement model evaluation emphasized reliability, validity, and construct assessment. Consistent with the two-stage hierarchical component modeling approach, the reflective first-order constructs were assessed in Stage 1 using CCA and then in Stage 2 multicollinearity for the formative second-order construct (BIM-JS) was assessed.

4.1.1 Stage 1: Reflective measurement model (CCA)

Indicator reliability

In this study, all first-order constructs were modeled as reflective (Mode A) composites within the PLS-SEM framework. The higher-order construct (BIM–JS) was assessed using the two-stage approach. During the first stage, the reliability of each indicator was evaluated by examining its factor loading (λ).

To improve reliability without compromising content validity, indicators with loadings below the recommended threshold of 0.708 were removed. This was done gradually, removing only one low-loading item at a time to preserve as much of the construct's content as possible. The item with the weakest loading (MF7) was eliminated first. The model was then re-estimated, and additional items with low loadings (OJ2, OJ3, and Col3) were removed in successive rounds. After four rounds of refinement, all remaining items met the required loading criteria (Table 3), and the measurement model was considered acceptable for further assessments.

Table 3: Stage-1 reflective loadings.

Construct	Loading λ	Construct	Loading λ
OJ1	0.879	Col1	0.853
OJ4	0.802	Col2	0.837
OJ5	0.884	Col4	0.786
MF1	0.756	Aut1	1.000
MF2	0.854	FB1	1.000
MF3	0.836	PS1	0.808
MF4	0.790	PS2	0.721
MF5	0.873	PS3	0.829
MF6	0.814	PS4	0.810

Internal consistency and convergent validity

Internal consistency and convergent validity of the reflective first-order constructs were assessed using CR and AVE. All multi-item reflective constructs met the recommended thresholds outlined in the methodology, with CR values exceeding 0.70 and AVE values above 0.50, indicating acceptable levels of reliability and convergent validity. For the single-item constructs—autonomy and feedback—internal consistency measures are not applicable; instead, their adequacy was evaluated based on their standardized loadings and content validity (Table 4).

Discriminant validity

Discriminant validity was assessed using both the Fornell–Larcker criterion and the HTMT ratio. According to the Fornell–Larcker criterion, the square root of the AVE for each construct was greater than its highest correlation with any other construct, indicating adequate discriminant validity. Specifically, the square root of AVE for BIM-JS (0.800) exceeded its correlation with Overall-JS (0.394), and the square root of AVE for Overall-JS (0.861) similarly exceeded its correlation with BIM-JS. Additionally, HTMT values were all well below the conservative threshold of 0.85, with the highest observed HTMT being 0.395. These results confirm that the latent constructs

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in the model are empirically distinct from one another.

Table 4: Construct reliability and convergent validity (reflective first-order constructs).

Construct	CR	AVE
Meaningfulness	0.925	0.674
Collaboration	0.758	0.512
Pain Points	0.871	0.629
Overall-JS	0.891	0.733
Autonomy (1 item)	n/a	n/a
Feedback (1 item)	n/a	n/a

4.1.2 Stage 2: Formative second-order construct (BIM-JS)

Multicollinearity

VIF was examined to assess collinearity among the formative first-order constructs forming the second-order BIM-JS construct. All VIF values were below the recommended threshold of 3.3, indicating no critical collinearity issues (meaningfulness = 2.12; collaboration = 2.58; autonomy = 1.46; feedback = 1.66; pain points = 2.36).

Formative weights significance (Bootstrapping)

Outer weights of the formative indicators were assessed using bootstrapping with 5,000 resamples. Most formative dimensions (Meaningfulness, Collaboration, Feedback, and Pain Points) showed significant outer weights at $p < .05$, confirming their contribution to the second-order BIM-JS construct. Autonomy did not exhibit a significant outer weight ($p = .274$), suggesting a weaker contribution. In line with recommended practice, outer loadings were also considered when interpreting the substantive relevance of this dimension (Table 5).

Table 5: Formative weights and significance for the BIM–JS higher-order construct.

First-Order Dimension	Outer Weight	t-value	p-value	Significance
Meaningfulness	0.312	6.148	< .001	Significant
Feedback	0.378	2.418	.016	Significant
Autonomy	0.089	1.030	.274	Not significant
Collaboration	0.385	4.716	< .001	Significant
Pain Points	0.232	4.778	< .001	Significant

4.2 Structural model evaluation

4.2.1 Model fit, R^2, f^2, and Q^2

Global model fit was acceptable, with an SRMR of 0.089. The model explained a modest yet meaningful share of variance in Overall Job Satisfaction ($R^2 = 0.163$; $f^2 = 0.195$, medium) and exhibited medium predictive relevance with $Q^2 = 0.175$. Collectively, these findings indicate credible explanatory power and out-of-sample performance.

Overall, the measurement model is statistically sound and suitable for further analysis. Reflective items showed strong reliability, and the constructs demonstrated adequate internal consistency, convergent validity, and discriminant validity. The formative assessment also indicated that each first-order dimension contributed unique information to the second-order BIM-JS construct without problematic collinearity. Together, these results confirm that the model meets key quality criteria and is appropriate for subsequent hypothesis testing.

4.3 Hypothesis testing

In the analysis for RQ1/H1, we examined which work factors contribute most to BIM-JS. Four factors—Collaboration, Meaningfulness, Pain Points, and Feedback—had significant effects, indicating that each plays an important role. Collaboration had the strongest effect (weight = 0.385), followed by Feedback (0.378), Meaningfulness (0.312), and Pain Points (0.232). Autonomy had the lowest weight (0.089) and was not statistically significant at the α = .05 level. These results support H1a, H1b, H1d, and H1e, but not H1c (Table 6).

Table 6: Hypothesis testing (H1).

Hypothesis	Dimension	Outer weight	t-value	p-value	Decision
H1a	Meaningfulness	0.312	6.148	< .001	Supported
H1b	Feedback	0.378	2.418	.016	Supported
H1c	Autonomy	0.089	1.030	.274	Not supported
H1d	Collaboration	0.385	4.716	< .001	Supported
H1e	Pain Points	0.232	4.778	< .001	Supported

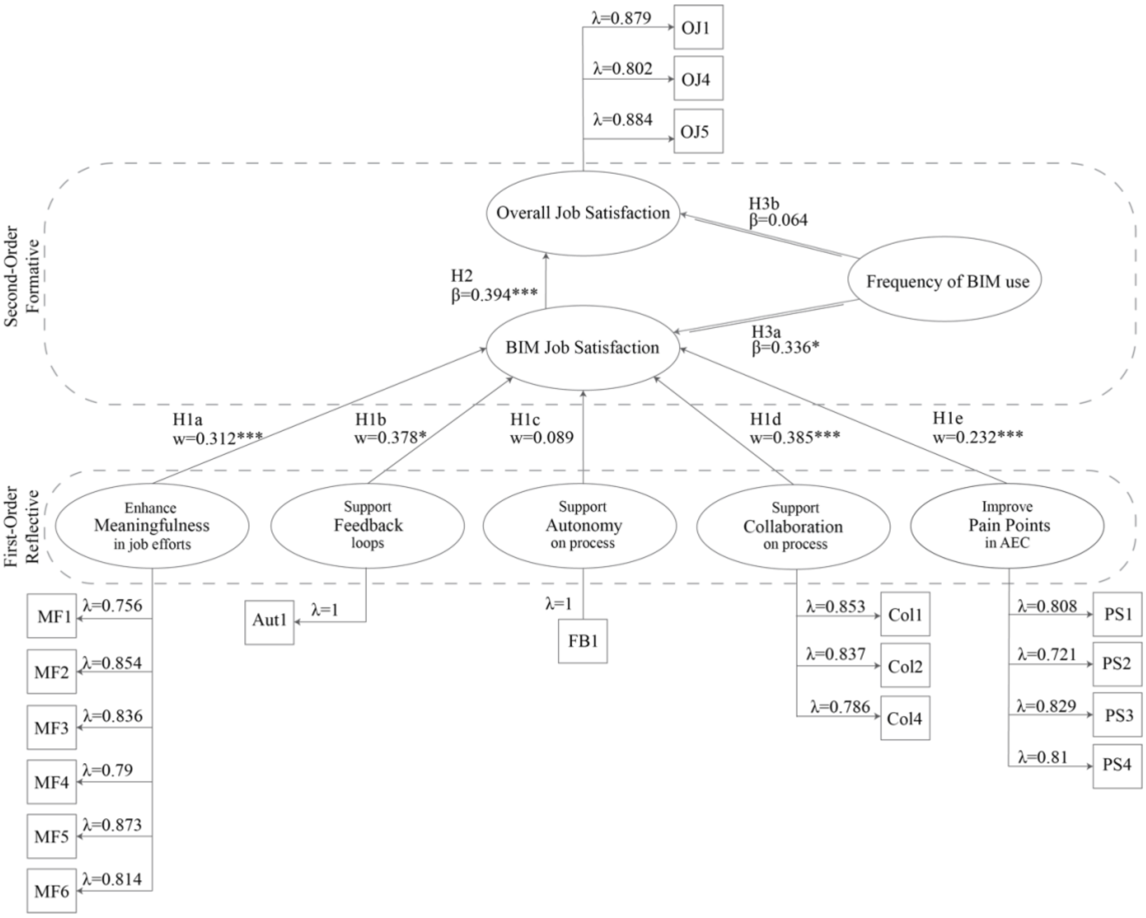

*Figure 3: SEM results. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.*

For RQ2/H2, we tested whether BIM-JS significantly predicts Overall Job Satisfaction. The structural path was positive and statistically significant (β = 0.394, t = 5.159, p < .001), and the bias-corrected 95% confidence interval [0.296, 0.583] did not cross zero, confirming the robustness of this effect. BIM-JS explained 16.3% of the variance in Overall-JS ($R^2 = 0.163$), with a medium effect size ($f^2 = 0.195$). Predictive relevance was also supported ($Q^2 = 0.175$), indicating that the model performs well in terms of out-of-sample prediction. These findings support H2 (Table 7).

It was also tested whether the frequency of BIM use affects job satisfaction. BIM use frequency significantly predicted BIM-related job satisfaction (BIM-JS), and BIM-JS, in turn, significantly predicted overall job satisfaction (Overall-JS) (Figure 3). However, BIM use frequency did not have a significant direct effect on Overall-JS. Bootstrapping of the indirect path (Frequency → BIM-JS → Overall-JS) indicated a statistically significant mediation effect (β = 0.126; 95% bootstrap CI did not include zero), supporting the hypothesized

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indirect pathway through BIM-JS (Table 7). The model explained 11.3% of the variance in BIM-JS and 16.3% of the variance in Overall-JS. Overall, these findings suggest that simply using BIM more frequently does not, by itself, improve overall job satisfaction; rather, frequency of use enhances job satisfaction primarily when it is associated with more positive BIM-related work experiences (Table 7).

Table 7: Hypothesis Testing (H2, H3).

Hypothesis	Path	β	t-value	p-value	Result
H2	BIM-JS → Overall-JS	0.394	5.159	< 0.001	Supported
H3a	Frequency → BIM-JS	0.336	2.53	<0.05	Supported
H3b	Frequency → Overall-JS	0.064	0.53	>0.05	Not Supported
H3c	Frequency → BIM-JS → Overall-JS	0.126	2.09	<0.05	Supported

5. DISCUSSION

This study investigated how BIM-enabled work practices shape job satisfaction in the AEC sector. The results provide strong evidence that BIM influences employee satisfaction primarily through improvements in collaboration, meaningfulness, feedback, and the reduction of pain points in daily tasks. Also, the findings suggest that the impact of BIM depends less on frequency of use and more on how it transforms day-to-day work.

Although BIM-JS significantly predicts Overall-JS, this relationship should be interpreted as an incremental contribution rather than a comprehensive explanation of job satisfaction. BIM-JS explained 16.3% of the variance in Overall-JS ($R^2 = 0.163$) with a medium effect size ($f^2 = 0.195$), indicating that BIM-enabled work conditions account for a meaningful but partial share of employees' overall satisfaction. Discriminant validity results further support that BIM-JS and Overall-JS are empirically distinct constructs rather than a part-whole hierarchy. Therefore, BIM primarily influences overall satisfaction through the job conditions it reshapes, while substantial variance remains attributable to non-BIM organizational and personal factors. The following discussion explores these outcomes in detail and considers their implications for both practice and future research.

5.1 RQ1: BIM factors' influence on BIM-JS

BIM's role in enhancing meaningfulness was a key contributor to BIM-JS. Professionals reported greater satisfaction when BIM enabled them to contribute visibly to team and client outcomes, expand their skills, and reinforce a sense of purpose. This alignment between personal development and collective impact appears to deepen satisfaction. Organizations seeking to support this factor should position BIM not merely as a technical tool but as a purpose-driven system that enables professionals to acquire new knowledge, apply their expertise, and ultimately observe the tangible outcomes of their efforts. This aligns with previous studies suggesting that when work technologies are designed to enhance job meaning and support intrinsic work values, they can increase engagement and satisfaction (Laschke et al., 2020).

Feedback showed a strong and positive effect on BIM-JS. This suggests that BIM is more satisfying when it helps professionals see the consequences of their decisions and receive timely responses from collaborators or downstream users. This aligns with the idea that digital models are not just design tools but communication and learning tools—when model updates, clash detection, and visualizations provide clear feedback loops, users feel more in control and more aware of their performance. The magnitude of the weight suggests that feedback is nearly as influential as collaboration and meaningfulness, highlighting the importance of using BIM processes and platforms to make outcomes and errors visible in a constructive way.

Autonomy emerged as the only non-significant predictor of BIM–JS. Although BIM technologies offer extensive data and decision-support capabilities, the results indicate that autonomy does not have a substantial impact on job satisfaction in this context. One possible explanation is that shared decision-making is essential for maintaining project coordination in BIM-enabled workflows, which may reduce the perceived importance of individual autonomy. Notably, this perceived limitation did not negatively affect overall job satisfaction. Instead, the findings suggest that in BIM-driven environments, professionals derive greater fulfillment from collaboration than from independent control, possibly highlighting the inherently social nature of BIM-enabled work practices.

Among the factors of BIM-JS, collaboration emerged as the most influential driver. BIM's inherent collaborative features can foster information sharing, joint problem-solving, and coordinated workflows; even modest improvements in perceived collaboration were linked to meaningfully higher job satisfaction. This underscores that to enhance job satisfaction, it is important to cultivate internal and external collaboration. This aligns with de Souza et al (2023), who emphasized that BIM workflows inherently depend on collaboration, making it essential to foster a cooperative environment consistent with AEC industry work patterns. Similarly, another study highlights that insufficient support for collaborative teamwork can hinder effective BIM adoption (Kapogiannis & Sherratt, 2018). The findings of this research reaffirm that collaboration is not merely a byproduct of BIM, but a central mechanism through which BIM enhances work experience.

Pain point reduction, while a more moderate contributor, was still a significant predictor of satisfaction. The responses to survey questions specific to pain points indicated BIM's ability to minimize rework, reduce manual tasks, support smoother workflows, and lower stress from tight deadlines. These findings highlight the importance of intuitive, user-centered design in BIM tools for reducing pain points.

This suggests that organizations seeking to enhance job satisfaction should not only promote advanced BIM features, but also use BIM to reduce day-to-day pain points, thereby reinforcing the perception that BIM solves real problems rather than adds to employees' workload.

5.2 RQ2: BIM-JS influence on overall-JS

In response to the second research question, this study examined how BIM-JS influences Overall-JS in the AEC industry. The findings indicate a moderate, positive relationship between BIM-JS and Overall-JS. In this study, higher scores on BIM-related meaningfulness, feedback, collaboration, and reduced pain points were associated with higher BIM-JS, which in turn significantly predicted Overall Job Satisfaction (Tables 5–7; Figure 3). This suggests that when BIM enhances core aspects of work, such as task clarity, feedback, collaboration, and smoother workflows, professionals report greater satisfaction.

5.3 RQ3: Frequency of BIM use and overall-JS

In addition to these factor-level insights, the mediation analysis further clarifies how BIM use translates into satisfaction. The effect of BIM use on Overall-JS operated primarily through BIM-JS: more frequent BIM use significantly increased BIM-related job satisfaction, and BIM-JS in turn significantly predicted Overall-JS, while the direct effect of BIM use frequency on Overall-JS was not significant. This pattern indicates that using BIM more often does not, by itself, improve overall job satisfaction unless it is accompanied by more positive BIM-related work experiences. Organizations should therefore prioritize not merely expanding BIM usage but ensuring that BIM is implemented in ways that enhance day-to-day work quality and satisfaction. Doing so can promote sustained engagement and job fulfillment, reinforcing BIM's value as a human-centered tool for organizational growth.

Taken together, these results indicate that the value of BIM extends beyond its technical functions to the quality of the work experience it enables. Our BIM-JS Measurement Model demonstrates moderate predictive power and theoretical coherence, suggesting that BIM shapes not only how professionals complete their tasks but also how they feel about their work. Positive BIM experiences, especially around collaboration and meaningfulness, appear to elevate broader attitudes and strengthen work enjoyment.

5.4 Implications

These findings extend the JCM and related job-satisfaction frameworks into the BIM context, indicating that digital tools are associated with more positive work experiences. Higher perceived meaningfulness and collaboration are key factors of BIM-mediated job satisfaction in contemporary AEC environments. From a managerial perspective, successful BIM adoption depends not only on technical deployment but also on cultivating a collaborative work culture. Our results indicate that satisfaction in BIM-enabled environments is driven more by shared engagement and reduced workflow stress than by greater individual autonomy. Accordingly, leadership should prioritize and create opportunities for enhancing collaboration through fostering teamwork, strengthening both internal and external communication, and facilitating smoother collaborative workflows to enhance overall employee satisfaction. This can be supported through structured mechanisms for cross-disciplinary coordination. Fostering meaningfulness involves linking day-to-day BIM tasks to broader project outcomes and client objectives, helping users see the significance of their work. BIM can also serve as a platform that clarifies the task purpose while enabling knowledge exchange and mutual support among users.

Workflow pain points represent another critical area requiring attention. BIM is designed to reduce friction in project delivery, but its potential is only realized when users are equipped to apply it effectively. Managers should focus on resolving pain points, such as tight deadlines, manual drafting, and design clashes, through the effective use of BIM tools. In parallel, structured feedback systems such as real-time design review tools or automated progress tracking can enhance learning, recognition, and long-term job enjoyment.

These insights suggest that improving the quality of BIM engagement rather than simply increasing its frequency is key to improving employee satisfaction. Training and implementation strategies should emphasize how BIM enables collaboration, supports feedback, and clarifies task ownership. Encouraging professionals to build a more meaningful relationship with technology can deepen their sense of purpose and motivation. From a theoretical standpoint, these findings reinforce the importance of considering human-centered factors, not just adoption rates, when evaluating digital transformation outcomes. In the context of the AEC industry, BIM should be understood not only as a project management tool but also as a platform for shaping professional experiences, satisfaction, and long-term workforce engagement.

5.5 Limitation and future direction

While this study offers meaningful insights into how BIM-related work experiences influence job satisfaction, several limitations should be considered when interpreting the results. The sample size (n = 86), though adequate for PLS-SEM, was relatively small and included for both public and private sector professionals. A larger sample would strengthen the generalization of the findings and allow for results to be disaggregated by the work sector. The sample also includes limited contractor representation, which constrains the study's ability to capture lifecycle-wide BIM experiences across construction and operations roles. Future research should test the BIM-JS framework with more balanced samples across architects, engineers, contractors, subcontractors, and facility management professionals.

Moreover, focusing on BIM-enabled organizations, the sample primarily represents post-adoption BIM contexts and should not be generalized to the broader AEC workforce, particularly non-BIM or pre-adoption populations. The research can continue to incorporate a more diverse range of AEC professionals to achieve a more comprehensive and representative sample.

From another perspective, Overall-JS is a global evaluation; it is influenced by many factors beyond BIM (e.g., compensation, workload, leadership, organizational justice, and personal circumstances). Therefore, the modest variance explained (R^2 = 0.163) indicates that BIM-related work conditions are one contributor among many. Future studies should test BIM-JS alongside broader controls and competing predictors to better estimate BIM's incremental contribution.

Because the study relied on cross-sectional, self-reported data, it cannot establish causal relationships with certainty. Although the BIM-JS Measurement Model demonstrated good predictive validity, the directionality of the associations was guided by theory rather than confirmed through empirical testing. Longitudinal or quasi-experimental designs could provide a more robust understanding of how BIM-JS develops over time. Qualitative approaches, such as interviews or case studies, would also help contextualize these dynamics and uncover nuanced user experiences. Autonomy and feedback were operationalized using single-item indicators, which may introduce differences in measurement precision compared with multi-item constructs. Although these items were theoretically grounded and capture clearly defined job characteristics, they may have limited the depth and reliability of the analysis. Future studies should refine these factors using validated multi-item scales to better capture their complexity and improve measurement precision.

Finally, the study focused on professionals working in the United States. BIM implementation and its impact on job satisfaction may vary across cultural, regulatory, and organizational contexts. Comparative studies across different countries or regions would provide valuable insights into how local factors shape digital adoption and its human-centered outcomes in the AEC sector. Taken together, these considerations highlight the need for broader, context-sensitive, and methodologically diverse research to deepen and extend the current findings.

6. CONCLUSION

This study underscores the significant role of BIM not only as a technical innovation but as a factor in shaping positive work experiences in the BIM-enabled AEC workplace. By integrating Hackman and Oldham's JCM with AEC-specific challenges, the proposed BIM-JS Measurement Model reveals that collaboration, meaningfulness, feedback about job performance, and the alleviation of workplace pain points are critical drivers of job satisfaction in BIM-enabled environments. However, autonomy, while traditionally emphasized in job satisfaction models, did not show a significant effect, suggesting that BIM's collaborative allowances may reframe the value of independent control in favor of shared coordination. The findings affirm that job satisfaction in digital workspaces hinges less on the frequency of technology use and more on the quality of engagement it fosters, particularly in terms of team collaboration and reduced workflow friction.

More broadly, the results support a human-centric approach to digital transformation in construction, where technological tools are evaluated not solely for their productivity gains but for their impact on well-being and professional fulfillment. For industry leaders and practitioners, this highlights the importance of implementing BIM with a focus on training, team communication, and purposeful design rather than relying on adoption alone. Future research should build upon these insights by incorporating larger, more diverse samples and longitudinal data to better capture the evolving relationship between digital tools and human experience across varying BIM-use intensities and organizational contexts. Ultimately, placing people at the center of digital innovation remains essential for creating sustainable, satisfying, and resilient workplaces in BIM-enabled segments of the AEC sector.

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