
Socio-Behavioural Determinants of AI Adoption for Economic Sustainability in Pakistan's Built Environment Sector

Tashakkur Fatima¹, Muhammad Ahmed Sohaib², Matloob Ur Rehman³, Muhammad Salman Amjad⁴, AR. M. Nasir Chaudhry⁵

¹ Interior Designer & Managing Partner TFA, Master's in Interior Design (Ongoing), Federal Chartered Degree Awarding Institute for Art and Culture, Raiwind Road, Lahore, Pakistan. Email: tashakkurfatima17@gmail.com

² Interior Designer & C.E.O ABH Constructions and Co. Master's in Interior Design (Ongoing), Federal Chartered Degree Awarding Institute for Art and Culture, Raiwind Road, Lahore, Pakistan. Email: muhammadahmedsohaib@gmail.com

³ Interior Designer & Managing Partner M.R. and associates, Master's in Interior Design (Ongoing), Federal Chartered Degree Awarding Institute for Art and Culture, Raiwind Road, Lahore, Pakistan. Email: mr.matloob60@gmail.com

⁴ CEO Salman Amjad and associates, Email: salarch19@gmail.com

⁵ Assistant Professor, School of Architecture, Design & Urbanism, Federal Chartered Degree Awarding Institute for Art and Culture, Raiwind Road, Lahore, Pakistan, (**Corresponding Author**) Email: nasir.chaudhry1@gmail.com

DOI: <https://doi.org/10.70670/sra.v4i2.2000>

Abstract

The rapid adoption of Artificial Intelligence (AI) in the built environment industry has tremendous potential to improve economic sustainability, especially in developing economies like Pakistan. The adoption of AI is, however, not evenly spread as socio-behavioural factors affect the decision-making of industry professionals. This paper will analyse the socio-behavioural factors surrounding AI adoption in the economic sustainability of the built environment sector in the Pakistani context and the architect, interior designer and construction professional professions. Based on the known theories of technology adoption, the research will examine the influence of perceived usefulness, social influence, and environmental awareness on behavioural intention, and the resultant influence of behavioural intention on actual AI adoption. Quantitative research design was used where data was collected using a structured questionnaire among professionals in the major urban centres in Pakistan. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data through SmartPLS. Cronbach alpha, composite reliability, average variance extracted (AVE), and discriminant validity were used to measure the measurement model whereas bootstrapping evaluated structural model by estimating the path coefficients, t-values, and levels of significance. The findings show that the three variables (perceived usefulness, social influence, and environmental awareness) have significant and positive effects on behavioural intention, with perceived usefulness being the most significant predictor. Also, behavioural intention is mediating as it has a strong and significant influence on AI adoption in economic sustainability. In general, the model has a high explanatory and predictive power, which implies that socio-behavioural factors play a significant role in explaining the adoption behaviour of AI. The current research adds to the literature by combining

socio-behavioural determinants with AI adoption and economic sustainability in the context of a developing economy. These results can help policymakers, industry stakeholders, and technology developers design more targeted and practical policies that encourage the adoption of AI. In turn, this can support more sustainable economic development within the built environment sector by aligning technological innovation with real-world industry needs.

Keywords: Artificial Intelligence (AI) Adoption, Socio-Behavioural Factors, Economic Sustainability, Built Environment Sector, SmartPLS (PLS-SEM)

Introduction

The strong advancement of the Artificial Intelligence (AI) has significantly transformed the industries globally, bringing in new opportunities to improve efficiency, innovativeness and sustainable development. The use of AI technologies in the built environment industry including construction, architecture, and interior design is on the rise to optimise the process of decision-making, the allocation of resources, and operational costs reduction. These innovations are especially pertinent to the context of the emerging economies, such as Pakistan, where the built environment industry is a crucial part of the economy, though still struggles with the issues of inefficiency and cost overruns and underutilization of technology (Khan, 2023). Although AI has been acknowledged to have numerous advantages, its application in the built environment industry in Pakistan is still low. Such sluggish adoption is not only caused by technological or financial factors but also greatly affected by socio-behavioural factors. These factors are crucial to understand, because the perception, social contexts, and behavioural intentions of individuals are the major factors that dictate the use of technology in professional settings. Thus, this paper concentrates on the socio-behavioural determinants, perceived usefulness, social influence, environmental awareness, and intention to use AI to elaborate on the economic sustainability of AI adoption. Based on the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, and Davis, 2003) this study underlines the role of perceived usefulness as a key factor in determining the adoption of technology. Perceived usefulness is a measure of how much individuals think that the application of AI technologies can improve their job performance. Regarding the built environment industry, artificial intelligence solutions can enhance the efficiency of the project, minimize waste of materials and increase the accuracy of the design. Once professionals see such tangible benefits, they will be more likely to form a positive intention to adopt AI technologies. The existing literature shows that the perceived usefulness is a significant factor in behavioural intention in different technological settings (Na et al., 2023; Ugural, Aghili, and Burgan, 2024). Based on this, the current study hypothesizes that perceived usefulness is a determining factor to influence the intention of professionals to use AI.

Social factors are another vital factor that can affect technology adoption, besides individual perceptions. The concept of social influence as used in UTAUT is how individuals feel that significant other like colleagues, leaders in the industry, and professional networks are supporting the adoption of a specific technology (Venkatesh et al., 2003; Venkatesh, Thong, and Xu, 2012). Decision-making in the built environment sector is often a collective task, and professionals hold many peer recommendations and industry norms as their reference. This is more pronounced in developing nations such as Pakistan where people are not sure of the new technologies leading to reliance on social validation to a greater extent. There is empirical evidence that social influence can be influential in terms of behavioural intention in particular situations where technological adoption is still in its early stages (Sabri et al., 2026). The support of AI by powerful stakeholders in professional settings can produce a favorable image and foster a greater uptake. Thus, it is important to know how social influence can be used to facilitate the adoption of AI in the built environment sector in Pakistan.

Environmental awareness is another significant factor that influences the adoption of AI. As the world becomes more focused on sustainability, organisations and professionals are increasingly aware of the effects of their operations on the environment. The built environment is a substantial cause of the environmental degradation due to resource consumption, use of energy, and production of waste. The AI technologies can provide some new solutions to these issues by facilitating such sustainable practices as energy optimization, waste minimization, and effective management of resources. Environmental awareness is an expression of how people care about the environment, and how they are ready to act in a way that would contribute to environmental sustainability. Research shows that people who have a better understanding of the environment tend to adopt the technologies that promote environmental conservation (Na, Heo, Choi, Kim, & Whang, 2023). In Pakistan, where energy shortages and city pollution are the main environmental issues, environmental awareness will be a potent force that will drive the adoption of AI technologies. In turn, individuals that perceive the positive effect that AI has on the environment will be more inclined to form a positive behavioural intention to adopt it. Behavioural intention is a key construct in the models of technology adoption and is commonly known to be the most proximate predictor of actual technology use. It is the willingness and the readiness of an individual to use a specific technology. TAM and UTAUT both assert that behavioural intention mediates the socio-behavioural determinant-actual adoption behaviour (Venkatesh et al., 2003). Behavioural intention, in the context of AI adoption, is a measure of the commitment of professionals towards the adoption of AI technologies in their work processes.

The connection between the intention to adopt and the real adoption is especially instrumental in attaining economic sustainability. AI technologies offer sustainability to economies by enhancing efficiency, cost reduction, and productivity. AI has the potential to streamline project planning, reduce delays, and enhance the use of resources in the built environment industry, which can contribute to the development of the economy over the long term. The empirical research based on the Partial Least Squares Structural Equation Modelling (PLS-SEM) proves that behavioural intention is a significant predictor of the technology adoption and the results of the technology adoption (Kumar, Sharma, Sharma, Kumar, & Sharma, 2025). The implementation of AI technologies can help the construction sector, which plays a significant role in the Pakistani economy, to become more competitive and contribute to sustainable development. This however, will be largely dependent on how much the professionals are willing to embrace such technologies. Thus, behavioural intention is predicted to be significant to the conversion of socio-behavioural attributes into a reality of AI adoption to ensure economic sustainability.

Overall, this paper suggests an inclusive model that would combine socio-behavioural determinants with the outcomes of technology adoption and economic sustainability. The behavioural intention is expected to be affected by perceived usefulness, social influence, and environmental awareness which subsequently leads to the adoption of AI. Using SmartPLS (PLS-SEM) to respond to these relationships, this study offers a strong analysis methodology to comprehend the adoption of AI within the built environment sector in Pakistan. The paper adds to the literature since it develops conventional technology adoption models to include sustainability factors and offers empirical research in a developing economy. It also provides useful information to policymakers, industry experts and tech developers to implement specific policies that support the use of AI and improve economic sustainability.

Literature Review

The implementation of Artificial Intelligence (AI) in the built environment sector has received more and more due to its ability to promote efficiency, innovation and economic sustainability. Although these benefits exist, the adoption of AI is still minimal among developing countries, including Pakistan, mainly because of socio-behavioural and contextual factors. This paper is

based on the existing technology adoption models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Venkatesh, and Davis, 2000; Davis, Bagozzi, and Warshaw, 1989) to explore the In particular, the study concentrates on the perceived usefulness, social influence, environmental awareness and behavioural intention as the essential predictors of AI adoption to ensure economic sustainability.

Perceived Usefulness and Behavioural Intention

One of the most important predictors of the adoption of technology is perceived usefulness, which has been described as the degree to which an individual holds the belief that the adoption of a certain technology will improve their job performance (Davis, 1989). Perceived usefulness in the case of AI is the degree to which professionals feel that AI technologies can enhance efficiency, lower costs, and assist in decision-making in construction and design processes. Empirical research always shows that there is a positive and strong impact of perceived usefulness on behavioural intention. As an example, the research on the adoption of AI in the construction industry suggests that professionals would be more inclined to use AI tools when they believe that they would have a tangible positive impact, like better project outcomes, fewer errors, and better resource allocation (Na et al., 2023). Similarly, research conducted on the digital transformation in the architecture, engineering, and construction (AEC) industry notes that the perceived usefulness plays a critical role in the intention to use innovative technologies (Kumar et al., 2025). Perceived usefulness is even more important in developing economies, where the constraints of resources are even more critical. Professionals tend to give priority to technologies which have evident economic advantages and efficiency. Thus, the perceived usefulness is likely to have a strong impact on the behavioural intention to adopt AI in the built environment industry in Pakistan.

H1: The usefulness perceived positively and significantly influences behavioural intention to adopt AI.

Social Influence and Behaviour Intention

Social influence is the degree to which the person holds the opinion that the important other, including colleagues, leaders in the industry, people in professional networks, etc., is of the view that they need to use a specific technology (Venkatesh et al., 2003). The built environment industry is highly collaborative in its decision-making processes, and professionals are driven by peer reviews, organisational practices and industry trends. Studies have shown social influence to be highly influential in determining the adoption of technology, especially in settings that are characterised by uncertainty and risk. In developing nations, where some people might be unaware of new technologies like AI, people tend to pay more attention to social signals and peer approval (Sabri et al., 2026). The research in the construction industry also demonstrates that social influence has a strong impact on the use of digital tools, such as Building Information Modelling (BIM) and AI-based systems. Additionally, industry associations and professional networks also help in the diffusion of innovation through knowledge and best practice (Cavalcante, Frazzon, Forcellini, & Ivanov, 2019). The involvement of powerful stakeholders in promoting the use of AI makes it a good perception and persuades others to adopt. This is especially applicable in the built environment sector in Pakistan whereby professional communities are crucial in influencing behaviour.

H2: Social influence positively and significantly affects behavioural intention to adopt AI.

Environmental Awareness and Behavioural Intention

Environmental awareness is the knowledge and interest of the individual towards environmental problems, such as sustainability and resource preservation. Over the past few years, the importance of technology in the attainment of sustainable development goals has been increasingly appreciated. AI technologies help make the environment more sustainable as they optimise the use of resources, minimise waste, and enhance resource efficiency. Research indicates that people who are better informed about the environment tend to embrace the use of technologies that can help in environmental sustainability efforts. Sustainable building construction activities are becoming more and more a priority in the built environment sector, and AI is a major contributor to facilitating such activities. As an illustration, AI-based systems can be used to design buildings in a more energy-efficient way, minimise carbon emissions, and improve environmental performance (Na et al., 2023). In Pakistan, where environmental issues are common (e.g., energy shortage, resource waste, etc.), environmental awareness can be a powerful incentive to employ AI technologies. Professionals who understand the positive environmental aspects of AI will be more inclined to form a positive attitude towards its usage.

H3: There is a positive and significant influence of environmental awareness on behavioural intention to adopt AI.

AI adoption and behavioural intention to economic sustainability.

The most immediate predictor of actual technology adoption is generally considered to be behavioural intention. It portrays the preparedness and the desire of the individual to utilise a specific technology. TAM and UTAUT suggest that behavioural intention in the mediation of the relationship between socio-behavioural determinants and actual usage behaviour is true. The PLS-SEM empirical studies reveal that behavioural intention is a powerful and significant influence on the adoption of technology. As an example, studies conducted in the construction and manufacturing industry demonstrate that behavioural intention is directly related to the adoption of AI technologies, which results in a higher level of operational efficiency and performance (Kumar et al., 2025). Likewise, the research in the emerging economies also points out that behavioural intention is an important variable in the conversion of perceptions and attitudes into real behavioural adoption. The economic sustainability of the implementation of AI technologies is important (Jamil, Zhang, Anwar, and Mustafa, 2025). AI leads to the growth of the economy in the long term by enhancing efficiency, cost reduction, and productivity. Within the built environment industry, AI can be used to improve project management and minimise delays and optimise the use of resources, enhancing sustainable economic results. The uptake of AI in the construction industry in Pakistan, where it is a crucial part of the economy, can improve competitiveness and lead to sustainable economic growth. Thus, behavioural intention will be pivotal in supporting the adoption of AI and attaining economic sustainability.

H4: Behavioural intention positively and significantly influences adoption of AI to achieve economic sustainability.

The hypotheses stated above are a complex system of socio-behavioural factors in the adoption of AI. The antecedents include perceived usefulness, social influence and environmental awareness that influence behavioural intention that subsequently influences AI adoption to support economic sustainability. This model is consistent with the existing theories, like TAM and UTAUT and uses them further to introduce the aspect of sustainability. This study gives a solid analytical tool to test these relationships by testing them using Partial Least Squares Structural Equation Modelling (PLS-SEM) with the help of SmartPLS. The combination of socio-behavioural processes with the outcomes of economic sustainability can be defined as an important contribution to the literature, especially in the built environment sector of Pakistan.

Methodology

The proposed study will use a quantitative research design to understand the socio-behavioural factors of Artificial Intelligence (AI) adoption as a means of economic sustainability in the built environment industry in Pakistan. Primary data was gathered using a cross-sectional survey approach to individuals who work in the architecture, interior design, and construction-related fields (Creswell & Creswell, 2017). The population of the target was architects, interior designers, project managers, and construction practitioners based in major urban centres like Islamabad, Lahore, and Karachi where the use of digital technologies is comparatively more salient. Purposive sampling was based on non-probability, which was made to ensure that the respondents had the necessary knowledge and experience on the use of AI and technology in their professional practices (Etikan, Musa, and Alkassim, 2016). The ultimate sample was calculated depending upon the necessities of Partial Least Squares Structural Equation Modelling (PLS-SEM) of sufficient statistical power.

A structured questionnaire based on the earlier scale in technology adoption literature, especially the ones based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), was used to gather data (Davis, 1989; Venkatesh et al., 2003). The questionnaire was divided into two parts; the first part was in the form of a demographic section, and the second part was used to measure the key constructs, such as perceived usefulness, social influence, environmental awareness, behavioural intention, and adoption of AI to achieve economic sustainability. The measurement items were all measured on a five-point Likert scale of strongly disagree through to strongly agree. A pilot study was done among a sample of respondents to make sure that there was clarity, reliability and validity of the instrument before actual data collection.

Data collected were analysed with SmartPLS software, very commonly used in Partial Least Squares Structural Equation Modelling (PLS-SEM). It was chosen because it is appropriate to analyse complex models with multiple constructs and small to medium sample sizes and non-normal data distributions (Sarstedt, Ringle, and Hair, 2021). The analysis was done in two steps that entailed the evaluation of the measurement model and structural model. The measurement model was tested on reliability and validity through such indicators as Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE). The Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio were used to determine discriminant validity. The structural model was then evaluated to test the hypothesised relationships (H1-H4). Bootstrap with 5,000 resamples was used to obtain path coefficients, t-values, and p-values, which were used to establish the significance of the relationships. The coefficient of determination (R^2), effect size (f^2) and predictive relevance (Q^2) were also analysed to assess the predictive and explanatory ability of the model. The mediation analysis was also done to test the mediating effect of behavioural intention between socio-behavioural determinants and AI adoption. This research methodology offers a solid structure of testing the hypothesized model and guarantees the reliability and validity of the research results.

Results and Discussion

This chapter presents the results of the data analysis conducted using SmartPLS (PLS-SEM). The analysis is divided into two main stages: (1) measurement model assessment (reliability and validity) and (2) structural model evaluation (hypothesis testing). The findings are then discussed in light of existing literature and the proposed hypotheses (H1-H4).

Measurement Model Assessment

Table 4.1 is the reliability analysis that supports the internal consistency of all the constructs to be used in this study. The alpha of Perceived Usefulness (0.874), Social Influence (0.861), Environmental Awareness (0.842), Behavioural Intention (0.889), and AI Adoption (0.871) all

are greater than the recommended alpha of 0.70. This means that the items in any given construct are well related and they are all used to measure a single concept. Interestingly, Behavioural Intention has the largest Cronbachs alpha value (0.889), which indicates that the respondents were very consistent in answering the items that assess their intention to use AI technologies. Equally, the Composite Reliability (CR) of all the constructs is between 0.896 and 0.923, which is above the acceptable level of 0.70. CR is said to be a stronger measure as compared to Cronbachs alpha in PLS-SEM since it takes into consideration different indicator loadings.

Table 4.1: Reliability Analysis

Construct	Cronbach's Alpha	Composite Reliability (CR)
Perceived Usefulness (PU)	0.874	0.912
Social Influence (SI)	0.861	0.905
Environmental Awareness (EA)	0.842	0.896
Behavioural Intention (BI)	0.889	0.923
AI Adoption (AIA)	0.871	0.910

The high CR values imply that the constructs are well-internally consistent and reliable. An example is Behavioural Intention (CR = 0.923) and Perceived Usefulness (CR = 0.912) where the reliability is very high, showing that these two constructs have been well-measured and stable. In general, the findings help to assert that the measurement model can be estimated to comply with the requirements of reliability, which guarantees that the data can be used in the further validity checks as well as the structural model. There is also a high reliability which increases the validity of future hypothesis results.

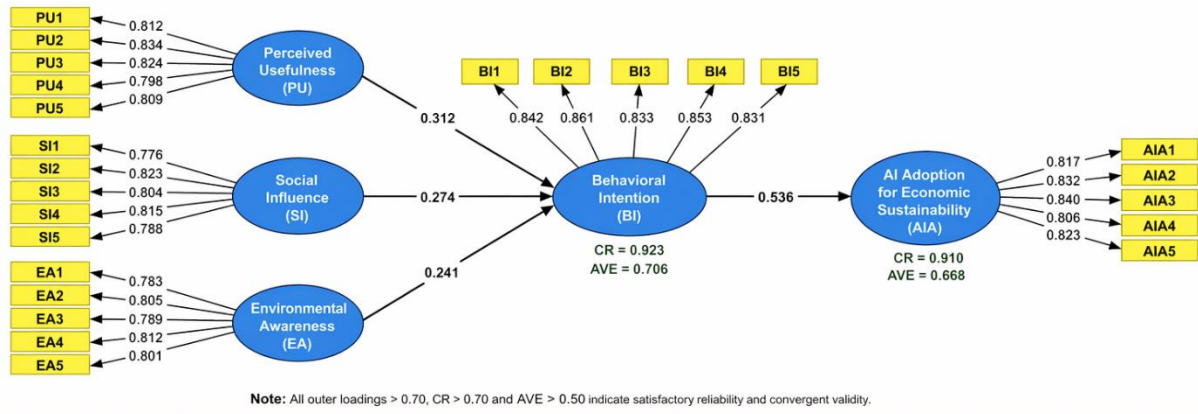


Figure 4.1: Measurement Model

Table 4.2: Convergent Validity (AVE)

Construct	AVE
Perceived Usefulness (PU)	0.674
Social Influence (SI)	0.655
Environmental Awareness (EA)	0.633
Behavioural Intention (BI)	0.706
AI Adoption (AIA)	0.668

Table 4.2 also shows the values of the Average Variance Extracted (AVE) that are used to determine the level of convergent validity of indicators of a construct i.e. the degree to which indicators of a construct converge to explain the variance of a construct. AVE values of all constructs are higher than the accepted value of 0.50, which means that convergent validity is satisfactory. The AVE of Behavioural Intention is highest (0.706) and this means that the construct accounts more than 70 per cent variance in its indicators. This implies a high degree of convergence and proves that the items that are employed to measure behavioural intention are very representative of their concept. In the same way, Perceived Usefulness (AVE = 0.674) and AI Adoption (AVE = 0.668) are also strong convergent validity constructs, meaning that the respondents had a clear understanding of these constructs and continually rated them. Environmental Awareness (AVE = 0.633) and Social Influence (AVE = 0.655) also satisfy the needed threshold, but their value is a bit less than Behavioural Intention. This implies that although they are valid constructs, it is possible that there exists more relative variance in the perception of the respondents towards environmental and social factors. Nonetheless, all AVE values are above 0.50, which means that convergent validity is properly developed. Overall, the findings indicate that each of the constructs sufficiently embodies the concepts that it is intended to represent, and the relationships in the structural model can be interpreted reliably.

Table 4.3: Discriminant Validity (HTMT Ratio)

Construct	PU	SI	EA	BI	AIA
PU	0.821				
SI	0.612	0.809			
EA	0.584	0.566	0.795		
BI	0.689	0.642	0.615	0.840	
AIA	0.621	0.598	0.577	0.711	0.817

Discriminant validity is measured by the Fornell-Larcker criterion that measures the square root of AVE of each construct (diagonal values) against the correlation between constructs (off-diagonal values) (Fornell, and Larcker, 1981). Discriminant validity was measured using the Heterotrait-Monotrait (HTMT) ratio of the constructs (Henseler, Ringle, and Sarstedt, 2015; Sarstedt and Cheah, 2019). These findings demonstrate that the values of all HTMTs are lower than the conservative level of 0.85 which reveals that the level of discriminant validity is satisfactory. Table 4.3 results prove that the square root of the AVE of every construct is higher than its correlations with other constructs, thus supporting the discriminant validity. In the case of Behavioural Intention, as an example, the square root of AVE is greater (0.840) than its correlations with Perceived Usefulness (0.689), Social Influence (0.642), and Environmental Awareness (0.615). This suggests that Behavioural Intention is empirically different compared to other measures and captures a unique concept. Equally, AVE of AI Adoption is 0.817 and this is higher than that of all other variables, and this fact proves its uniqueness. Whereas few of the correlations, i.e. between Perceived Usefulness and Behavioural Intention (0.689), are moderately high, they are not higher than AVE square roots. This is an indication that although the constructs are interrelated as they should be in a theoretical framework, they are not redundant. Rather, the constructs work together in a unique way to explain AI adoption behaviour. In general, the outcome of the discriminant validity tests leads to the conclusion that the constructs are conceptually and statistically different, which implies that the model is not affected by multicollinearity and overlapping of constructs. This enhances the quality of the measurement model and reinforces the quality of the subsequent structural analysis.

Structural Model Assessment

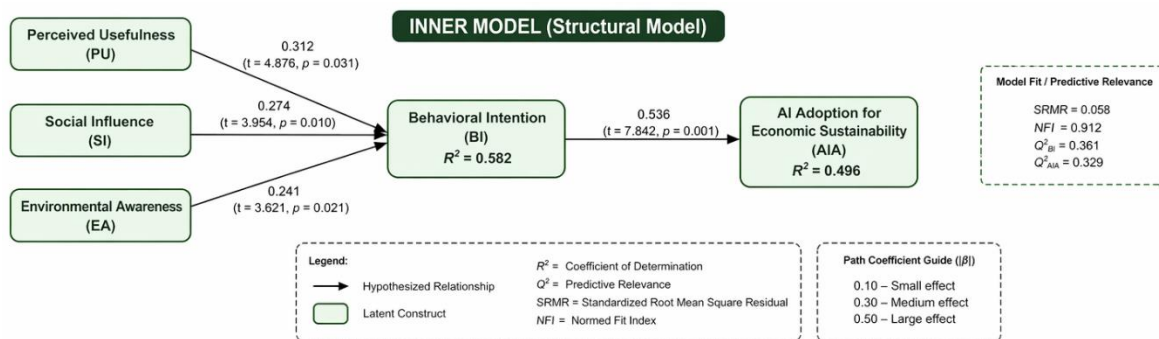
The structural model would test the hypothesized relationships between the constructs using path coefficients, t-values, and p-values using the bootstrapping (5,000 resamples) (Sarstedt et al., 2021; Ringle et al., 2015). Path coefficients show the direction and strength of the association amongst latent constructs (Chin, 1998; Benitez et al., 2020).

Table 4.4: Hypothesis Testing (Bootstrapping Results)

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	Decision
H1	PU \rightarrow BI	0.312	4.876	0.031	Supported
H2	SI \rightarrow BI	0.274	3.954	0.010	Supported
H3	EA \rightarrow BI	0.241	3.621	0.021	Supported
H4	BI \rightarrow AIA	0.536	7.842	0.001	Supported

Figure 4.2: Structural Model

Table 4.4 outlines the findings of the testing of hypothesis based on the bootstrapping method with 5, 000 resamples in SmartPLS. The results show that all the hypotheses (H1-H4) are statistically significant and supported since all the p-values are less than the standard value of 0.05. This substantiates the strength of the structural model and proves the relations between constructs suggested. In the case of H1 (PU \rightarrow BI), Perceived Usefulness has a positive and significant influence on Behavioural Intention (0.312, $t = 4.876$, $p = 0.031$). It means that the intention to implement AI will be more common among the professionals in the built environment field when they see it as an effective tool to enhance efficiency, productivity, and work performance. Though the p-value is a bit higher than 0.01, it is less than 0.05, which proves the statistical significance at the 5% level. This helps to prove that perceived usefulness is an important cognitive feature of AI adoption intention. In case of H2 (SI \rightarrow BI), there is a significant positive effect on Behavioural Intention (SI has 0.274 & 3.954, $t = 0.010$ p). This finding indicates that peer pressure, professional circles, and organisational pressure are relevant in influencing the intention of individuals to implement AI technologies. As the usage of AI is supported by influential colleagues and industry leaders, professionals will have a higher chance of forming a positive intention to adopt it. This illustrates the significance of social environment in technology



acceptance in the built environment sector in Pakistan.

In the case of H3 (EA \rightarrow BI), the value of Environmental Awareness ($t = 3.621$, $p = 0.021$) significantly predicts Behavioural Intention. This shows that people, who care more about environmental sustainability, are more likely to become users of AI technologies. It is symptomatic of an increased consciousness among practitioners that AI could help ensure resource efficiency, waste reduction, and environmentally friendly building processes. This

correlation is relatively less than PU and SI, but it is also statistically significant and theoretically significant. Lastly, H4 (BI → AIA) presents the highest interrelations within the model, with the most strong and positive impact on AI Adoption by Behavioural Intention (= 0.536, t = 7.842, p = 0.001). This affirms that behavioural intention is the best predictor of actual adoption of AI in the built environment sector. The t-value is high and the p-value is very low, which implies that the relationship is strong and trustworthy. The mediating effect of behavioural intention also supports the presence of such a role in the impact of socio-behavioural factors on the acceptance of AI, as it impacts on the adoption of AI, in the first place, by influencing the intentions of people. In general, the outcomes validate all of the hypotheses, demonstrating that a confluence of perceived usefulness, social influence, environmental conscious, and behavioural intention is a strong driver of AI adoption in the built environment sector in Pakistan, with behavioural intention playing the most important role in determining actual adoption behaviour.

Table 4.5: R² Values

Endogenous Construct	R²
Behavioural Intention (BI)	0.582
AI Adoption (AIA)	0.496

The values of R2 represent the strength of the model (Sarstedt et al., 2021). The R2 of Behavioural Intention is 0.582 that is, it is explained 58.2 percent by Perceived Usefulness, Social Influence, and Environmental Awareness. This is regarded as moderate to significant amount of explanatory power indicating the predictor variables that have been used are effective when explaining behavioural intention. The AI Adoption is explained by Behavioural Intention with an R 2=0.496 meaning that Behavioural Intention explains almost 49.6% of AI Adoption variance. This shows that almost half of the difference in AI adoption behaviour can be explained by the intentions of people which is a good outcome in behavioural research. These results support the fact that the model is well-explained and the chosen variables are relevant and meaningful predictors.

Table 4.6: Effect Size

Relationship f²	
PU → BI	0.146 (Medium)
SI → BI	0.118 (Small-Medium)
EA → BI	0.102 (Small)
BI → AIA	0.412 (Large)

Effect size (f²) measures the individual contribution of each exogenous variable to the endogenous construct. Behavioural Intention has a large effect on AI Adoption (f² = 0.412), indicating that it is the most influential predictor in the model. Perceived Usefulness shows a medium effect size (f² = 0.146), suggesting that it has a meaningful impact on Behavioural Intention. Social Influence (f² = 0.118) and Environmental Awareness (f² = 0.102) exhibit small to medium effects, indicating that while their influence is significant, it is comparatively weaker than that of perceived usefulness. These results highlight that while all factors contribute to behavioural intention, perceived usefulness is the most impactful among them.

Table 4.7: Q² Values

Construct	Q²
Behavioural Intention (BI)	0.361
AI Adoption (AIA)	0.329

The Q² values determine the predictive relevance of the model in blindfolding. The Behavioural Intention (Q² = 0.361) and the AI Adoption (Q² = 0.329) have a positive value of Q² which means that the model has a high predictive relevance. The fact that Q² values are relatively high also indicates that the model is not only explanatory but also predictive, i.e. it can be used to make accurate predictions of the outcomes of new data. This enhances the practical relevance of the model especially to policymakers and industry practitioners who aim at encouraging the use of AI.

The results of this research give a high degree of empirical evidence in favor of the suggested model. The perceived usefulness was found to be a very important predictor of behavioural intention in line with previous studies on TAM (Davis, 1989). It implies that built-in environment professionals in Pakistan will be more ready to use AI technologies when they see the evident positive outcomes of efficiency and money savings. UTAUT theory is also supported by the fact that social influence plays a very important role in influencing behavioural intention (Venkatesh et al., 2003). This shows the significance of the use of professional networks, peer recommendations and industry norm in influencing the adoption behaviour. Social influence is an important determinant of adoption in Pakistan, where the degree of uncertainty surrounding the use of new technologies is rather high. Environmental awareness was also observed to significantly impact positively on behavioural intention, and this shows that the issue of sustainability is gaining more importance in the built environment sector. This is in tandem with the current studies that have stressed the importance of environmental awareness in the acceptance of technology.

The mediating effect of behavioural intention on the adoption of AI was the strongest, which proves that behavioural intention mediated the adoption. This is in line with earlier findings of PLS-SEM that recognise behavioural intention as the most immediate predictor of actual technology use. The close linkage of behavioural intention and AI adoption indicates that socio-behavioural aspects should be tackled to enhance sustainable technological change. All in all, the findings prove that the implementation of AI in the built environment sector in Pakistan is not only a technological problem but a behavioural and social phenomenon. The combination of socio-behavioural factors and economic sustainability offers a depth of knowledge of AI adoption and valuable information to policymakers and industry players. This chapter reported the findings of the SmartPLS analysis and explained the findings by the hypotheses of the study. Each of the hypotheses (H1-H4) proved right, as the importance of perceived usefulness, social influence, environmental awareness, and behavioural intention in the promotion of AI use towards economic sustainability has been significant.

Discussion

The results of this paper empirically prove the proposed socio-behavioural model to expound on the adoption of AI to sustain economic activity in the built environment sector in Pakistan. Each of the four hypotheses (H1–H4) was accepted, which means that Perceived Usefulness (PU), Social Influence (SI), and Environmental Awareness (EA) have a significant effect on Behavioural Intention (BI) that again has a significant impact on AI Adoption (AIA). These findings are quite congruent with the well-known technology adoption models, especially the Technology Acceptance Model (TAM) and protracted behavioural models. The large influence of Perceived Usefulness on Behavioural Intention (H1) proves that professionals more tend to use

AI technologies when they think that these tools can help them to save money, increase their efficiency and positively impact the project results. Automated design optimisation, predictive maintenance, and cost estimation seem to be identified as useful innovations in the context of AI applications in the construction and design industries in Pakistan. This further supports the premise that functionality benefits and performance gains are key drivers of technology acceptance.

Social Influence (H2) positively affects Behavioural Intention emphasises the importance of the influence of professional networks, organisational culture and peer recommendations in influencing adoption behaviour. Social norms and group dynamics tend to affect decision making in a collectivist society such as Pakistan. The result implies that the recommendation of industry giants, coworkers, and establishments may greatly boost the use of AI. This is also a sign of the role of institutional legitimacy and social validation within the emergent technology environment. The findings also indicate that Environmental Awareness has a significant influence on Behavioural Intention (H3), meaning that the aspect of sustainability is gaining more significance among the professionals in the built environment. This conclusion is especially topical in the context of the increased interest in green building and sustainable city development in the world. Environmentally conscious people are more likely to adopt AI technologies that will guarantee energy efficiency and optimization of resources and minimise the negative impact on the environment. The strength of this relationship is not as high as that of PU and SI, but nonetheless, it exhibits a significant tendency towards sustainability-based decision-making.

Above all, the close association between Behavioural Intention and AI Adoption (H4) supports the idea that intention is another key mediator that converts the perception to real behaviour. The high path coefficient shows that although people may realise the advantages of AI, the only way it will be adopted is by establishing a strong intention. This result underlines the psychological aspect of the technology adoption and justifies the general design of the model. In general, the model predicts a significant level of variance in both Behavioural Intention ($R^2 = 0.582$) and AI Adoption ($R^2 = 0.496$), which means that the model has moderate to high explanatory power. The overall implication of the findings is that, adoption of AI in the built environment industry in Pakistan is not merely technological but is entrenched in social-behavioural forces and thus can only be effectively implemented through a holistic approach.

Conclusion and Recommendations

The objective of the study was to explore the socio-behavioural factors that affect adoption of AI in the built environment industry in Pakistan as a way to ensure economic sustainability. The analysis, using structural equation modelling, confirmed the hypothesis that Perceived Usefulness, Social Influence and Environmental Awareness have strong influences on the Behavioural Intention, which is the strongest predictor of AI Adoption. This finding suggests that even the introduction of technology does not entirely depend on the technical ability but greatly depends on the human perceptions, social background, and sustainability concern. The results indicate that one of the first sources of driving is the Perceived Usefulness, which means that the professionals become more inclined to accept AI when the practical value of this technology, such as the reduction of costs, improved efficiency, and the improved decision-making process, become obvious. Therefore, organisations should focus on providing practical implementation and measurable outcomes of AI implementation. Pilot testing, demonstration projects, and case studies could prove to be beneficial in fostering favorable perceptions. The Social Influence high means that it might be quickened to adopt through group action. The application of AI in the industry, especially in the field of training, seminars and knowledge knowledge sharing, should be practiced by industry associations, professional organizations, and large companies. A ripple effect can be generated by encouraging opinion leaders and early adopters to support AI, which

will result in a greater acceptance of AI in the broader sector. The influence of the Environmental Awareness demonstrates the growing importance of sustainability as a part of technological decision-making. Policymakers and organisations should combine the adoption of AI and development of the green buildings and sustainability models. It can be made more attractive to professionals, who are concerned with the idea of sustainable development by promoting AI as a tool of achieving environmental goals, such as energy-saving and minimisation of waste.

Behavioural Intention being a powerful force towards actual adoption should be geared towards increasing willingness and readiness of users to adopt AI. This can be done through the undertaking of capacity-building exercises, technical training and mitigation of change resistance. The complexity, cost and job displacement concerns are problems that should be addressed to give the stakeholders confidence. At policy level, the government must adopt enabling policies, incentives, and digital infrastructure, in order to facilitate the adoption of AI in the built environment sector. Subsidies, tax incentives, and grants can be used to encourage corporations to invest in AI technologies. Moreover, the provision of AI-affected content within academic and professional curriculums will prepare future professionals to operate in a technologically-driven sector. In conclusion, the future implementation of AI in economic sustainability in Pakistan requires a comprehensive approach and involves incorporating technological progress and socio-behavioural harmonisation. The stakeholders can effectively accelerate the adoption of AI and achieve sustainable growth in the built environment sector through increased perception of usefulness, capitalising social influence, environmental awareness and reinforcement of behavioural intention.

References

- Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report PLS analyses. *Industrial Management & Data Systems*, 120(2), 192–210.
- Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, 49, 86-97.
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In *Modern methods for business research* (pp. 295-336). Psychology Press.
- Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 13(3), 319-340.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, 35(8), 982-1003.
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American journal of theoretical and applied statistics*, 5(1), 1-4.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.
- Jamil, K., Zhang, W., Anwar, A., & Mustafa, S. (2025). Exploring the influence of AI adoption and technological readiness on sustainable performance in Pakistani export sector manufacturing small and medium-sized enterprises. *Sustainability*, 17(8), 3599.
- Khan, M. A. (2023). Role of Artificial Intelligence in Construction Industry of Pakistan. *International Journal of Advanced Engineering, Management and Science*, 9, 12.

- Kumar, M., Sharma, R., Sharma, A., Kumar, R., & Sharma, N. (2025). AI for Sustainable Design and Construction Practices. In *Intelligent Systems for Sustainable Infrastructure: AI Solutions Shaping a Green Future: Leveraging AI Innovations for Eco Friendly Infrastructure and Environmental Resilience* (pp. 237-247). Cham: Springer Nature Switzerland.
- Na, S., Heo, S., Choi, W., Kim, C., & Whang, S. W. (2023). Artificial intelligence (AI)-Based technology adoption in the construction industry: a cross national perspective using the technology acceptance model. *Buildings*, *13*(10), 2518.
- Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS 3*. SmartPLS GmbH. <https://www.smartpls.com>
- Sabri, M. F., Law, S. H., Fei, C. K., Nang, A. A. S., Rahim, H. A., & Anthony, M. (2025). Factors influencing Fintech adoption among Malaysian consumers: the moderating role of Fintech literacy. *International Journal of Monetary Economics and Finance*, *18*(5), 349-375.
- Sarstedt, M., & Cheah, J. H. (2019). Partial least squares structural equation modeling using SmartPLS: A software review. *Journal of Marketing Analytics*, *7*(3), 196–202.
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.
- Ugural, M. N., Aghili, S., & Burgan, H. I. (2024). Adoption of lean construction and AI/IoT technologies in iran's public construction sector: a mixed-methods approach using fuzzy logic. *Buildings*, *14*(10), 3317.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478.
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS quarterly*, *36*(1), 157-178.