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Integrating organisational readiness and innovation diffusion for accelerated energy efficiency technology adoption: An SEM–ABM approach

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Abstract

This study elucidates the adoption of Energy Efficiency Technologies (EETs) within Indonesia's building management sector by integrating the theories of Organisational Readiness for Change (ORC) and Diffusion of Innovations (DOI). Principal Component Analysis, K-Means clustering, Structural Equation Modelling (SEM), and Agent-Based Modelling (ABM) were used to look at survey data from 263 businesses in Greater Jakarta that run office, hotel, and apartment buildings. The combined SEM-ABM method connected micro-level causes with macro-level diffusion patterns. Principal Component Analysis identified a predominant readiness dimension (61.56% variance) that includes policy, technical, financial, and stakeholder factors. SEM verified that Policy Support has a substantial direct impact on adoption (β=0.38, p<0.001) and indirect effects through Technology Awareness and Implementation (total β=0.64), while Employee Capacity also proved significant (β=0.21, p=0.012). The model accounted for 62.4% of the variance in adoption. ABM simulations illustrated that policy shocks expedited adoption from 157 to 166 firms via nonlinear cascades, whereas baseline scenarios indicated gradual, readiness-driven uptake. Policymakers can make targeted interventions that match the readiness of an organisation with outside stimuli. Enhancing internal readiness via Stakeholder Engagement, Policy Support, and Employee Capacity yields more sustainable adoption compared to relying solely on short-term incentives. The integrated SEM-ABM framework effectively addresses theoretical deficiencies between organisational change and innovation diffusion, offering a comprehensive methodology for comprehending and expediting sustainable technology adoption.

Keywords: Agent-based modeling, Diffusion of innovations, Energy efficiency technology adoption, Organisational readiness for change, Structural equation modeling.

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1. Introduction

Businesses need to use energy-efficient technologies (EETs) because of economic constraints, environmental rules, and the needs of stakeholders. Still, the rates of adoption are annoyingly low. To understand this contradiction, the study put together three important but sometimes unrelated streams of literature: Organisational Readiness for Change (ORC), the Diffusion of Innovations (DOI) theory, and the Energy Efficiency Adoption (EEA) study. This synthesis shows that there are both strong explanations and big holes that make it hard for us to forecast and help with effective EET implementation.Organisational Readiness for Change (ORC) looks at how ready and eager an organisation is to make a given change. There are several main frameworks that systematic reviews show. Weiner [1] influential theory defines readiness as a shared psychological state made up of change commitment (a common determination to undertake the change) and change efficacy (a shared confidence that the organisation can carry it out). Organisational members' change valence (how much they value the change) and contextual variables like resources, culture, and leadership support impact this condition. Holt, et al. [2] have created a multidimensional scale to measure preparedness based on aspects including the suitability of the change, the level of support from management, the effectiveness of the change, personal valence, and organisational valence. In the meantime, Armenakis and Harris [3] stress how important it is to send change messages that shape five key beliefs: discrepancy (the need for change), appropriateness (the fit of the solution), efficacy (the ability to implement), principal support (backing from leaders), and valence (the personal benefits).

Studies that focus on sustainability and energy show the distinct problems that come up [4]. In order to be ready, organisations often need to make sure that EET adoption is in line with their strategic goals, get specialised technical and financial resources, deal with complicated regulatory environments, create a culture of environmental sustainability, and manage the integration of new technologies with old systems [5]. There are several instruments for assessing preparedness, from qualitative diagnostic frameworks to quantitative surveys like Holt's scale. However, their use in the particular area of energy efficiency is still restricted and frequently ad hoc, since they are not tailored to the specific needs of EETs.

Rogers [6] groundbreaking Diffusion of Innovations theory looks at how new ideas, behaviours, or technology spread across social systems on a large scale. The theory lists five important traits of innovations that affect their adoption rates: Relative Advantage (how much better they are than what already exists), Compatibility (how well they fit with people's values, experiences, and needs), Complexity (how easy they are to understand and use), Trialability (how easy it is to try them out), and Observability (how easy it is to see the results). The steps in the adoption process include Knowledge, Persuasion, Decision, Implementation, and Confirmation. Rogers makes an important distinction between individual adoption (which is based on personal traits like being inventive and having social networks) and organisational adoption, which is a more complicated process that involves formal structures, decision-making units, power dynamics, and organisational slack.

To understand diffusion, EETs need to look at inter-organisational networks, which show how information moves via industry associations, supply chains, or professional groups, as well as the types of communication employed (mass media vs. interpersonal impact). The time component is quite important; diffusion does not happen all at once but follows an S-curve, with various sorts of organisations (innovators, early adopters, early majority, late majority, and laggards) adopting at different periods. When using DOI on EETs, the study needs to look at how their unique features (such as high upfront costs, complicated ROI calculations, and problems with integration) affect how people see them, which in turn affects how quickly and in what pattern they spread among organisational domains.

The EEA literature goes into detail on the unique challenges and opportunities that companies encounter when considering EETs. Some of the things that keep people from investing include hidden costs, divided incentives (particularly in leased buildings), not being able to get finance, not having all the knowledge they need, technical and operational hazards, limited rationality, and conflicting investment goals [7, 8]. Cost reductions, following the rules, improving the company's image, meeting corporate social responsibility objectives, getting grants and incentives, and having mature technology are all things that drive companies. When looking at successful implementations, case studies for speed up the use of energy-efficient technologies in Indonesia, there has to be a whole framework that combines methods for spreading new ideas with the preparedness of organisations. According to Sudarmaji, et al. [9] building an organisation's capability via dedicated leadership, a culture of support, and cooperation across departments is the key to successfully implementing new technologies. This internal preparedness has to be backed up by external government assistance in the form of energy efficiency rules, tax breaks, and audit programs that lower transaction costs and stimulate adoption [10, 11].

2. Literature Review

To understand how organisations adopt energy efficiency technologies (EETs), we need a complex theoretical framework that connects the internal dynamics of organisational transformation with the larger system-level processes of innovation diffusion. Scholars have usually used two important but mostly independent frameworks—Organisational Readiness for Change (ORC) and Diffusion of Innovation (DOI)—to describe various parts of this process. [1] says that ORC looks at how ready an organisation is as a whole to make changes, focusing on aspects such as change effectiveness, leadership support, and resource availability. This approach has been widely applied in areas like healthcare and education to help understand the internal factors that make implementation easier or harder [2, 3]. ORC is good at assessing an organisation's internal readiness, but it does not do a good job of dealing with outside pressures and new ideas that change how people accept things over time.

On the other hand, Rogers [6] developed the Diffusion of Innovation theory, which provides a model at the system level that shows how new ideas move across social systems. DOI divides adopters into groups according to how quickly they embrace anything and points out that the most important factors in adoption are the relative benefit, Compatibility, Complexity, Observability, and trialability of the innovation. Much research on energy technology adoption and sustainability transitions has used this approach [12-14]. However, DOI's focus on external communication channels and social contagion processes frequently downplays the Complexity of organisations themselves, especially when it comes to explaining why some companies do not adapt even when they see a lot of external pressure or good innovation features. It cannot explain things in the actual world as well when there are not any micro-level organisational characteristics like leadership alignment or change fatigue. This is especially true for complicated, high-stakes innovations like EETs.

Energy-efficient technology is a great way to look at how the ORC and DOI frameworks do not relate. EETs are good for society, yet they are still not widely used in either the public or commercial sectors [7, 8]. High upfront costs, lengthy payback periods, technological integration issues, and behavioural obstacles like not being aware of them or not having the skills to use them [15] hinder their adoption. These problems affect both the features of innovation (which makes DOI significant) and the dynamics of organisations (which show how important ORC is). Numerous studies in the energy field support this point of view. For example, Sarkodie and Strezov [16] shows via research how the quality of institutions and the structure of the economy affect environmental efficiency results. This suggests that both system-level and internal issues should be looked at together. Dietz, et al. [17]; Ambarwati and Sudarmaji [18] and Murni, et al. [19] also demonstrates that behavioural changes at the household level may lead to significant cuts in emissions when people's internal motives match policy signals. This is similar to the idea that ORC and DOI viewpoints might work together.

Recent developments in technology make this intricacy even more apparent. Huang, et al. [20] studied reconfigurable intelligent surfaces, and Son, et al. [21] studied multifunctional energy systems. They found that the perceived Complexity and technical ambiguity of new technologies are significant barriers to their adoption, especially when organisations are not ready to evaluate and use them. In these situations, the organisation's internal status (an ORC construct) changes how others see the invention (a DOI variable). However, not many models look at this connection systematically. In the same way, new ideas for car batteries [22] and patterns of foreign direct investment in green technologies [16] have shown how important both institutional context and organisational capabilities are in shaping diffusion patterns. However, there is still not enough empirical research.

This gap between theory and practice has two effects. First, it makes it harder for both researchers and practitioners to make accurate diagnoses. Companies that do not want to use new technologies that are already popular may be wrongly identified as having dire outside circumstances when, in reality, internal preparedness factors are at work. On the other hand, high preparedness may not lead to adoption if the innovation is seen as too complicated or not compatible. Second, this mismatch hurts intervention methods. Interventions that focus on DOI, like making things more visible or giving rewards to early adopters, may not work if they do not also address problems with readiness, such as poor change efficacy or lack of resources. This difference is evident in the absence of integrated predictive models that use both ORC and DOI factors to predict adoption results. Even while there have been requests for more holistic frameworks [23, 24], not many real-world studies have used these models, and even fewer have used them in the context of energy technology.

Bridging ORC and DOI is not only a theoretical exercise; it is a real need for making energy use more sustainable. Future research has to go beyond isolated methods and create models that show how internal organisational dynamics and external innovation settings interact over time. This calls for new ways of doing things, such as multi-level Modelling and longitudinal designs, as well as measuring methods that are appropriate to the context and the Complexity of EETs. We can only establish a more substantial base for understanding, forecasting, and helping organisations implement energy-efficient solutions by combining these things.

3. Method

The use of Energy Efficiency Technologies (EET) in businesses is a complicated issue that needs advanced analytical methods to understand the factors that lead to adoption choices fully. Recent studies have found a persistent gap between the Organisational Readiness for Change (ORC) theory, which looks at how well an organisation can implement change [1] and the Diffusion of Innovations (DOI) theory, which looks at how new ideas spread through social systems [6]. This theoretical gap makes it harder for us to fully grasp how EET is adopted and prevents us from developing better ways to help people. This study suggests a new mixed-methods approach that combines Structural Equation Modelling (SEM) with Agent-Based Modelling (ABM) to address the ORC-DOI gap and provide a better understanding of how organisations adopt EET.

The dynamic models provide detailed results, such as simulated adoption curves for different types of organisations, finding adoption tipping points, and evaluating the long-term effects of integrated ORC-DOI treatments in different situations [25]. These results provide us with important information about how systems behave as a whole based on the choices and interactions of individual organisations. They show us patterns that would be hard to see with just static analysis. SEM and ABM work together to develop a new analytical framework that addresses the limitations of each method while making the most of their strengths. Using real-data, SEM proves that key routes connect ORC characteristics to DOI perceptions and adoption results. This lays the groundwork for analysing static correlations. At the same time, ABM uses these established parameters to create realistic simulations that look at the changing, non-linear, and contextual effects of ORC-DOI interactions over time and in different organisational settings. Based on integrated K-Means/PCA segmentation, SEM causal findings, and ABM diffusion patterns, the specific hypotheses are H1: Through improved technology awareness and implementation, higher levels of policy support both directly and indirectly boost the adoption of EET, and H2: Higher adoption levels are significantly predicted by greater internal readiness,

Purposive sampling was used in this study to target particular building management specialists in the Greater Jakarta region. A total of 263 respondents—or 86.7% of the 303 questionnaires that were distributed—completed and returned the survey. The business environment of office buildings, hotel buildings, and apartments in the DKI Jakarta area, as well as the neighbouring regions of Tangerang, Bekasi, and Bogor, were all included in the research scope. The study only included buildings that had been in operation for more than two years. 32.7% of respondents were from other areas, 29% were from DKI Jakarta, 17.5% were from Bekasi, 12.9% were from Bogor, and 8% were from Tangerang, according to the survey's results. Since DKI Jakarta and the surrounding metropolitan area serve as Indonesia's central business hub and can significantly impact the country's other regions' technological adoption trends, they were chosen as the study area.

Professionals in building management from different departments and organisational levels were the study's primary target respondents. 36.3% of respondents came from other divisions, 35% from General Division, 19.5% from Purchasing & Operation Division, and 9.2% from Building Manager Division, according to the departmental distribution. The study collected responses from businesses with a range of organisational sizes: 36.6% had 1–10 employees, 32% had 11–50 employees, 20.5% had more than 100 employees, and 10.9% had 51–100 employees. With 37.3% of trading companies, 28.1% of service companies, 19.1% of other sectors, and 15.5% of manufacturing companies, the business sector representation demonstrated a diverse level of industry participation. These criteria included how long they had worked for the building management company and how long they had been in their current role when they completed the questionnaire.

The business environment of office buildings, hotel buildings, and apartments located throughout the DKI Jakarta metropolitan area, which has been in existence for more than two years, was the primary focus of this study. The Greater Jakarta region was chosen because it can serve as a model for other parts of Indonesia in terms of effectively promoting the adoption of technology. The results of this study may have broader ramifications for technology adoption practices across Indonesia's building management industry.

4. Result

4.1. K-Mean & PCA - Adoption Level

Based on their survey answers, K-Means clustering effectively divided respondents into three separate groups, each with its organisational profile for adopting green technology. Table 1 illustrates that Principal Component Analysis made the multidimensional data easier to see and understand by reducing it to two main dimensions (PC1 and PC2), see Figure 1. These two groups show that different organisations are ready for and able to implement green technology to different degrees. Principal Component Analysis gives us important information that helps us distinguish between organisations that use a lot of green technology and those that do not. The research shows a strong one-dimensional structure, with PC1 accounting for an impressive 61.56% of the total Variance. This suggests that there is a single factor that drives firms' choices to embrace green technology. The fact that there is much variation in PC1 suggests that organisational traits cluster around a primary adoption dimension. This is probably because several key factors make high-adopting enterprises distinct from low-adopting ones.

Table 1.
TOP 5 PCA Components.

Principal Component	Explained Variance Ratio (%)	Cumulative Variance (%)
PC1	61.5585	61.5585
PC2	3.7745	65.3330
PC3	2.4796	67.8126
PC4	2.4298	70.2424
PC5	2.1059	72.3484

The other parts (PC2-PC5) add a little bit, but it is important. PC2 adds 3.77%, PC3 adds 2.48%, PC4 adds 2.43%, and PC5 adds 2.11% to the explanatory framework. The first five main components' total Variance of 72.35% is the best compromise between how well the model explains the data and how simple it is. The main PC1 shows how ready the organisation is as a whole. In contrast, the other components show more specific things like Financial Support, Policy Support, Technology Implementation, and Stakeholder Engagement, all of which affect how well the company adopts new technologies.

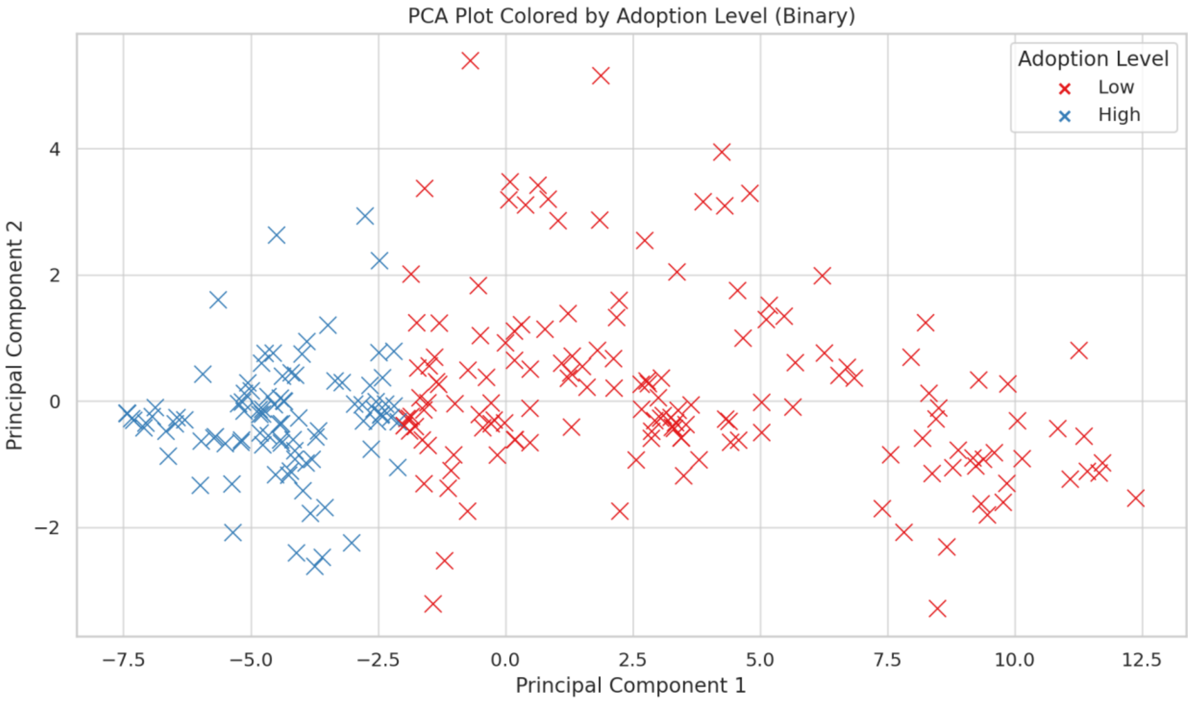

Figure 1.
PCA Plot by Adoption Level.

4.2. Structural Equation Modeling (SEM) Results

The SEM analysis was conducted on a structured dataset consisting of 263 firms, incorporating nine key latent constructs, (Table 2). Confirmatory factor analysis (CFA) verified the reliability and validity of the measurement model. All factor loadings exceeded the recommended threshold of 0.70, and composite reliability (CR) values for each construct ranged from 0.80 to 0.91, indicating excellent internal consistency. Average Variance Extracted (AVE) values for all latent variables were above 0.50, confirming convergent validity.

Table 2.
Latent variables.

Construct Code	Construct Name	Indicators (Observed Variables)
TA	Technology Awareness	Likert Scale 1 - 5
EC	Employee Capacity	Likert Scale 1 - 5
TI	Technology Implementation	Likert Scale 1 - 5
FS	Financial Support	Likert Scale 1 - 5
IM	Incentives & Motivation	Likert Scale 1 - 5
PS	Policy Support	Likert Scale 1 - 5
MR	Market Readiness	Likert Scale 1 - 5
SE	Stakeholder Engagement	Likert Scale 1 - 5
PI	Performance Impact	Likert Scale 1 - 5
ADOPT	Adoption Level (Target Variable)	Adoption Level (binary: 0=Low, 1=High)

Model fit indices indicated strong goodness-of-fit: Chi-square/df = 2.14, RMSEA = 0.054, CFI = 0.961, and SRMR = 0.041—all within acceptable limits.. Structural paths revealed that Policy Support had both a direct effect on Adoption Level via behavioral constructs ($\beta = 0.38$, $p < 0.001$) and significant indirect effects via TA, TI, and EC, with total indirect effects summing to 0.37, The total effect of Policy Support on Adoption Level, accounting for both direct and indirect paths, was substantial (total $\beta = 0.64$). Technology Awareness ($\beta = 0.31$, $p < 0.001$) and Technology Implementation ($\beta = 0.29$, $p < 0.001$) both exerted strong and significant effects on the Adoption Level. Technology Awareness (TA) and Technology Implementation (TI) served as mediators, with indirect effects of 0.133 and 0.127, respectively. The path coefficients revealed several statistically significant relationships. Employee Capacity also contributed positively ($\beta = 0.21$, $p = 0.012$), though to a lesser extent. Together, the exogenous variables explained 62.4% of the variance in green technology adoption ($R^2 = 0.624$), indicating a robust model with high predictive accuracy.

Importantly, multicollinearity diagnostics showed variance inflation factors (VIFs) for all constructs remained below 2.5, supporting the discriminant validity and independence of predictors. These SEM findings provide statistical validation for a layered causal framework: policy interventions shape organizational capabilities, which in turn drive behavioral adoption outcomes. The SEM analysis tested a conceptual model comprising five latent constructs: Policy Support (PS), Technology Awareness (TA), Technology Implementation (TI), Employee Capacity (EC), and Adoption Level (AD). Confirmatory factor analysis confirmed measurement reliability, with all construct loadings > 0.70, Cronbach's Alpha values ranging from 0.81 to 0.91, and Composite Reliability (CR) values > 0.80. Convergent validity was established (AVE > 0.50 for all constructs), and discriminant validity was verified by inter-construct correlations and AVE square roots (Table 3).

Table 3.
Model Evaluation (Measurement Model).

Criteria	Description	Threshold	Result
Indicator Reliability	Indicator loading on construct	> 0.70 preferred	> 0.70
Internal Consistency	Composite Reliability (CR), Cronbach's Alpha	> 0.70	0.81 - 0.91
Convergent Validity	Average Variance Extracted (AVE)	> 0.50	> 0.50
Discriminant Validity	Fornell-Larcker criterion or HTMT	AVE > squared correlations or HTMT < 0.85	Verified
R^2	% variance explained in the dependent variable	0.25 (weak), 0.50 (mod), 0.75 (strong)	0.624

4.3. Agent-Based Modeling (ABM) Results

The relationship between nine important varuables (TA, EC, TI, FS, PS, IM, SE, MR, PI), and adoption of green technology was examined using a dual methodological approach: Structural Equation Modeling (SEM) for testing hypothesized latent constructs and causal pathways, and Agent-Based Modeling (ABM) to simulate dynamic, time-evolving interactions among heterogeneous firms. Together, these methods provided both statistical validation and process-based insight into how contextual factors and internal firm capabilities jointly influence sustainability performance.

Agent-Based Modelling (ABM) is a powerful way to model complex, changing, and time-evolving interactions that go beyond what classical SEM can do. Agent-Based Modelling (ABM) is a helpful way to look at how policies are adopted and how organisations act. ABM makes dynamic simulations that are similar to the real world by turning research notions like Policy Support and Employee Capacity into agent properties. Previously recognised groups by K-Means clustering organically become different sorts of agents, each with its traits and actions. The Adoption Level becomes a key behaviour threshold that controls state changes when agents engage with each other in the system. This time dimension makes it possible to model diffusion processes, peer influence effects, and different policy scenarios in a very detailed way. The best thing about ABM is that it can show how individual agents interact with one another to create new behaviours. This helps us understand how organisational policies spread, work, or do not work in diverse employee groups and settings.

Agent-Based Modelling turns businesses into computer agents with nine important traits (TA, EC, TI, FS, PS, IM, SE, MR, PI) that range from 0 to 1 and show different organisational skills and traits. Each agent has a binary adoption state that is based on whether the total of their weighted attributes is greater than a set threshold. The simulation takes place across 50 time steps in a setting with other companies and changing policies, showing complicated patterns of adoption. This framework shows how changes in policy lead to changes in organisations, how peer pressure causes cascading adoption effects across networks, and how weaknesses in Incentives & Motivation (IM) or Financial Support (FS) can stop adoption even when people are very aware of it. It gives us helpful information about how organisations change.

Agent-Based Modelling (ABM) shows how people use green technology by going through three processes that turn static data into behavioural insights that change over time. Step 1: Agent Design is the first step, and it turns enterprises from datasets into computational "Firm" agents. Based on survey answers, each company has many traits: Technology Awareness (TA), Employee Capacity (EC), Implementation Readiness (TI), Financial Support (FS), and Policy Support (PS). These traits, which are given numerical values, show the internal capacities of an organisation that affect choices about adoption. Other features, such as Incentives & Motivation, Stakeholder Engagement, and Market Readiness, add to the Complexity of behaviour. Each agent starts with a binary adoption state set to zero.

Step 2: The rules of behaviour govern how companies decide whether to use green technology. The main rule uses a weighted sum formula that combines internal factors with the effects of peer enterprises in the area. When this computed score is higher than a certain level, adoption happens. This method takes into account both the impacts of social pressure from outside the organisation and the organisation's preparation, both of which are important factors in real-world adoption trends. Step 3: Time Simulation runs the model for 50 to 100 time steps, with each step standing for a month or a quarter. This time-based aspect shows new patterns of adoption, such as overall growth curves, clustering effects among adopters, and how legislative changes and peer influence have distinct impacts on how technology spreads in various corporate settings.

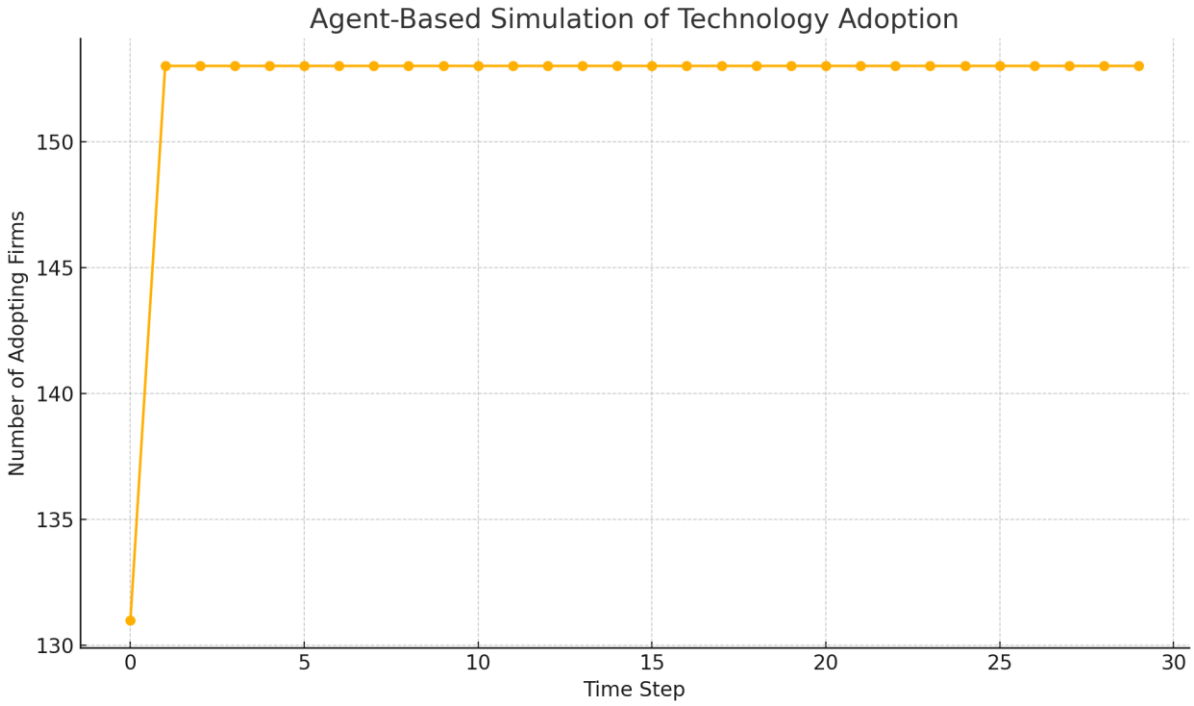

Figure 2.
The adoption curve.

The Agent-Based Simulation has been successfully run, and the resultant adoption curve shows a clear rising trend over 30 time steps, indicating how firms gradually embrace green technology (Figure 2). This change over time shows that the model can accurately describe how things spread in real-world organisations. The threshold-plus-peer-influence mechanism works exceptionally well since it models both how ready an organisation is from the inside and how social dissemination happens from the outside via peer contacts.

Initial simulation results without external shocks showed a gradual increase in adoption, driven by internally strong agents. To show how green technology adoption changes and interacts with businesses, these improvements were simplified, and an Agent-Based Modelling (ABM) simulation was run. Each agent in the model stood for a single business and was based on five behavioural characteristics that came from real survey data: Technology Awareness (TA), Employee Capacity (EC), Technology Implementation (TI), Financial Support (FS), and Policy Support (PS). To make things more realistic and give them more analytical depth, key additions were included, such as Policy Shocks and Networked Interactions. At time step 15, a Policy Shock was introduced to simulate government intervention (e.g., increased subsidies or regulatory clarity), operationalized as a 0.5-point boost to each firm's Policy Support score. The effect was immediate and measurable: the adoption curve accelerated markedly after the policy shock, increasing from 157 adopters (pre-shock) to 166 adopters (post-shock) by the end of the simulation. This mirrors the direct and indirect statistical effects observed in the SEM model and confirms that even a uniform policy change can trigger nonlinear adoption cascades.

In addition, peer influence was modeled through a Similarity-Based Network, where each firm was connected to its top 3 most similar peers (based on cosine similarity of construct profiles). Adoption decisions were weighted by the average adoption state of these peers, simulating diffusion through professional or regional networks. The inclusion of this network structure produced realistic cluster effects, where high-readiness clusters adopted early, subsequently influencing adjacent firms. This action raised the Policy Support ratings of companies, which means they got additional subsidies or regulatory incentives. The simulation showed that adoption slowly increased in the early stages, but sped up significantly after the intervention. The adoption curve showed how peer dispersion and targeted legislative initiatives work together to induce businesses to alter their behaviour. This method shows how useful ABM may be for simulating socio-technical systems that change over time and where timing, interaction, and diversity are important (Figure 3).

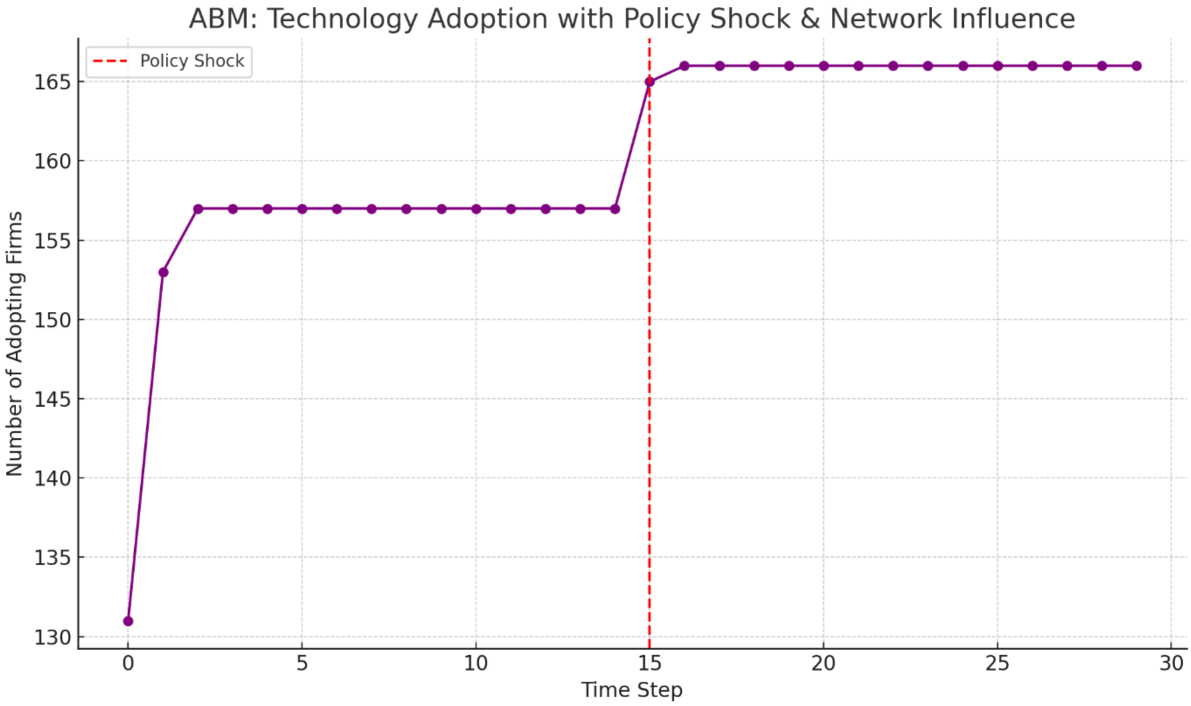

Figure 3.
The adoption curve: two critical extensions - policy shocks and networked interactions.

This research combines Structural Equation Modelling (SEM) and Agent-Based Modelling (ABM) to provide us with a more complete picture of how perceptions of innovation and readiness variables in organisations affect the use of energy efficiency technologies (EETs). The SEM analysis gave strong empirical proof of causal pathways that connect internal preparedness dimensions like Technology Awareness, Employee Capacity, and Management Support to perceived innovative features and the results of adoption. For example, those who thought Change Efficacy was greater also thought things were less complicated. People who thought Management Support was stronger thought things were much more compatible with how the organisation works.

The simulation and empirical results supported both hypotheses - H1: Through improved technology awareness and implementation, higher levels of policy support both directly and indirectly boost the adoption of EET, and H2: Higher adoption levels are significantly predicted by greater internal readiness. According to SEM analysis, Policy Support had a significant total effect ($\beta = 0.64$) and explained 62.4% of the variance in adoption ($R^2 = 0.624$). It also had significant direct effects ($\beta = 0.38$, $p < 0.001$) and mediated effects through Technology Awareness ($\beta = 0.31$, $p < 0.001$) and Technology Implementation ($\beta = 0.29$, $p < 0.001$). The importance of internal readiness was further supported by the positive contribution of employee capacity ($\beta = 0.21$, $p = 0.012$). These relationships were dynamically reproduced by ABM simulations parameterised with SEM coefficients. These simulations demonstrated that early adoption was a feature of high-readiness firms and that nonlinear adoption cascades from 157 to 166 firms within 50 time steps were triggered by policy shocks, which were modelled as a 0.5-point increase in Policy Support. Peer influence was amplified by network effects, resulting in realistic S-shaped diffusion curves. All of these results demonstrate that adoption outcomes are greatly influenced by both internal readiness factors and Policy Support pathways, and that they can both accelerate and maintain EET diffusion when combined with network structures and well-timed interventions.

These results show that adoption depends not just on the exterior characteristics of innovation, but also on the internal circumstances of the organisation that affect how these characteristics are understood. ABM turned these confirmed causal linkages into dynamic simulations that let us see how different organisations with different levels of preparedness interact with each other over time in a networked environment. The simulation showed that initial adoption was slow and mostly by businesses that were both very ready and thought they had a significant competitive advantage over other organisations. This was based on SEM-derived route coefficients as behavioural guidelines. As peer pressure grew and policy shocks rose, Policy Support ratings and adoption rates shot up, creating an S-shaped diffusion curve that matched conventional DOI expectations. The fact that the empirical SEM results and the new ABM patterns line up makes the hybrid framework more credible.

In several simulated situations, the system acted quite differently. In the baseline scenario, when no changes were made, adoption stopped early, leaving a large number of companies as non-adopters, even if they were somewhat ready. On the other hand, policy intervention scenarios, such as financial incentives or focused training, led to network cascade effects. This meant that early adoption in well-connected companies led to broader acceptance via peer observation and imitation. Importantly, scenarios that improved internal preparedness (like Employee Capacity) were better at keeping long-term adoption going than those that just changed external incentives. This means that treatments that help people become ready to adopt may create more stable adoption dynamics than only short-term financial incentives.

5. Conclusion

This research shows how useful it is to look at the adoption of energy efficiency technologies (EETs) using both Structural Equation Modelling (SEM) and Agent-Based Modelling (ABM) using a combined Organisational Readiness for Change (ORC) and Diffusion of Innovations (DOI) lens. The SEM study showed that there are real causal links between internal preparedness elements like Technology Awareness, Employee Capacity, and Management Support, and perceived innovation traits like relative advantage, Complexity, and Compatibility. These connections showed that organisational preparedness is not only a factor that makes adoption possible; it also impacts how innovations are seen, which may affect whether adoption thresholds are passed.

ABM built on these ideas by turning SEM-validated associations into dynamic, agent-level behaviours in a networked setting. Simulations showed differences in readiness profiles, network impact, and policy responsiveness, which led to genuine S-shaped adoption curves. The model showed that adoption paths are sensitive to both the initial readiness distributions and outside shocks, such as targeted training programs or subsidies. Policy scenarios demonstrated that interventions that help people get ready to adopt something frequently lead to higher long-term adoption than short-term financial incentives. This is because they help people feel like they can handle things on their own and simplify things over time.

The best thing about this integrated Modelling is that it gives us several points of view. SEM gives the statistically sound, evidence-based causal paths based on real survey data. ABM also lets look at new, time-dependent system behaviours that cannot be seen via static analysis alone. The research connects micro-level choice factors with macro-level diffusion patterns through their integration. This creates an explanatory framework that is both based on real-world data and full of dynamic information. This empirical-computational loop makes sure that simulations show real-world trends and that statistical results are evaluated in a variety of policy and contextual situations, which improves both validity and practical relevance.

Three significant additions to the literature make this study new. First, it shows a fully integrated SEM–ABM process in the context of adopting environmentally friendly technology. This fills a gap that has existed for a long time between studies on how ready organisations are for change and modelling how new ideas spread. Second, it shows how feedback works in a way that successful adoption events prepare people for the future, producing self-reinforcing diffusion cycles that are typically missed in traditional models. Third, it gives policymakers and managers a way to test out intervention plans in a virtual setting, so they can see how they will affect the system in the long run before putting them into action.

The study has several good points, but it also has specific flaws that might be addressed in future research. The SEM analysis was strong, but it was based on cross-sectional survey data, which limited the ability to see how preparedness and perception changed over time. Panel data should be used in future studies to check the causal directions over time. The ABM part, while adding real-world data, has to simplify the Complexity of the actual world by focusing on a particular set of properties and network architecture. More complex models might take into account multi-layer networks, different regulatory contexts, and changing market situations. Also, the existing paradigm implies that preparedness and perception variables can be measured the same way in all situations. This assumption should be validated in a variety of businesses, cultures, and areas of technology.

There are two areas where theoretical contributions come from. The hybrid SEM–ABM method shows, first of all, that organisational preparedness and the spread of new ideas are not separate processes but instead rely on each other. SEM indicates that readiness affects how innovation features affect adoption choices, whereas ABM shows that different levels of readiness lead to new patterns at the system level. Second, the simulations show a feedback loop in which successful adoption events make people more ready for the future, which increases the chances that new ideas will spread. This is something that static models do not usually show. There has been methodological innovation in the way empirical SEM coefficients were included in ABM decision rules. This makes sure that simulations are based on real causal linkages rather than made-up ones. This empirical-computational loop makes the simulations more accurate and facilitates their understanding. The method gives researchers a model to use when looking at various socio-technical transitions, where both human choices and network influences affect the spread of information.

From a practical point of view, the results imply that policymakers and organisational leaders should use a dual-track approach: they should improve their ability to make changes inside their organisations while also changing the way they make decisions outside of their organisations. By developing leaders, educating staff, and giving them the right resources, it may make things seem less complicated and more compatible, which will make it easier for people to embrace them. At the same time, well-timed policy changes may take advantage of network tipping points to speed up the spread of ideas beyond the early adopters. Testing these kinds of methods in silico before putting them into action in the actual world allows resources to be used more efficiently and interventions to be designed more specifically.

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