

# Deep SEM: Integrating deep neural networks into structural equation modelling with the SEMdeep package in R

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Isaac Osei<sup>1</sup> , Chettupally Anil Carie<sup>1</sup>, Bhaskar Marapelli<sup>2</sup>,  
Dennis Opoku Boadu<sup>3</sup>  and Satish Anamalamudi<sup>1</sup>

## Abstract

Structural Equation Modelling (SEM) has been widely applied in information systems, psychology, marketing, management, and other social science disciplines, providing a powerful framework for analysing relationships among latent variables. However, traditional SEM methods rely on assumptions of linearity and normality, which may limit their ability to represent complex or nonlinear data patterns. Recent advances in computational modelling have introduced Deep SEM (or Neural SEM), an approach that integrates deep learning components within SEM. This hybrid framework combines SEM's theoretical and explanatory strengths with the representational flexibility of neural networks. In this paper, we provide an overview of Deep SEM, demonstrate its implementation in R using the *SEMdeep* package, and compare its explanatory and predictive behaviour with that of a traditional covariance-based SEM under identical data conditions. Using an illustrative and parsimonious neural architecture, the results show that Deep SEM yields higher in-sample explained variance across endogenous constructs while preserving the dominant theoretical pathways identified by SEM. These findings suggest that Deep SEM offers a complementary extension to conventional SEM, enabling researchers to explore potential nonlinearities while maintaining interpretability and theoretical coherence.

## Keywords

SEMdeep, SEM, deep SEM, neural SEM, Structural Equation Modelling, artificial intelligence, machine learning, deep learning

## Introduction

Structural Equation Modelling (SEM) has become one of the most widely used analytical frameworks in applied research, particularly in information systems, psychology, education, business, marketing, and related social and behavioural sciences (Hair et al., 2019, 2022; Kline, 2016; Sarstedt et al., 2022). Its key strength lies in its ability to support the conceptualisation and empirical testing of complex latent variables (also called constructs) – unobserved theoretical concepts such as attitudes or perceptions – and the examination of theoretically grounded, often mediated, relationships among them. These conceptual goals are operationalised through measurement models, which link constructs to observed variables (indicators), and structural models, which specify directional relationships among constructs. This dual

capability has made SEM a central tool for theory testing, validation, and explanation across diverse research domains (Schamberger et al., 2025; Zheng, 2025).

Despite its widespread adoption, conventional SEM approaches face several well-documented limitations.

<sup>1</sup>Department of Computer Science and Engineering, SRM University-AP, Amaravati, Andhra Pradesh, India

<sup>2</sup>Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India

<sup>3</sup>Department of Computer Science, University of Ghana, Legon, Accra, Ghana

### Corresponding author:

Isaac Osei and Chettupally Anil Carie, Department of Computer Science and Engineering, SRM University-AP, Amaravati 522 240, Andhra Pradesh. Email: isaac\_osei@srmap.edu.in and anilcarie.c@srmap.edu.in



Standard SEM typically assumes linear relationships among latent variables, an assumption that may be overly restrictive in many real-world settings where nonlinearities and interaction effects are present (Irmer et al., 2024). In addition, SEM relies on distributional assumptions such as multivariate normality and often requires relatively large sample sizes to ensure stable estimation (Deng et al., 2018; Kline, 2016). From a predictive perspective, SEM is primarily designed for explanation rather than prediction, and its out-of-sample predictive performance is not typically the primary criterion of model evaluation, particularly when compared with flexible machine-learning approaches (Richter and Tudoran, 2024).

In response to these challenges, recent methodological research has explored hybrid approaches that integrate SEM with deep learning, commonly referred to as *Deep SEM* or *Neural SEM*. In this context, Deep SEM refers to a class of models in which the causal structure defined by SEM is retained, while the linear relationships between constructs are replaced or augmented by neural networks to allow for nonlinear effects. These approaches aim to preserve the theory-driven structure and interpretability of SEM while leveraging the flexibility and nonlinear approximation capabilities of deep neural networks (DNNs; Abbasi et al., 2021; Arpacı and Bahari, 2023; Mishra et al., 2024). Rather than replacing SEM, Deep SEM frameworks embed neural components within a predefined causal structure, allowing researchers to examine whether predictive performance can be improved without abandoning theoretical foundations.

In this paper, the term *Deep SEM* is used to denote structural equation models in which the structural component is estimated using deep neural networks, while the measurement model follows conventional SEM principles.

In this tutorial-oriented study, we demonstrate how the *SEMdeep* R package (Grassi, 2025) can be used to implement both conventional SEM and Deep SEM models within a unified workflow using open-source software, *R* (R Core Team, 2025). Importantly, the methodological framework itself is not proposed by this paper; instead, our contribution lies in providing a transparent, step-by-step illustration of how *SEMdeep* can be applied in practice and how its results can be interpreted alongside traditional SEM outputs.

To illustrate the workflow, we apply SEM and Deep SEM to a cryptocurrency-related dataset capturing key psychological and behavioural constructs associated with technology adoption. The empirical focus allows us to compare explanatory results (eg, path coefficients and model fit) with predictive performance, that is, the ability of the model to accurately predict endogenous constructs in unseen data under identical theoretical specifications. Particular attention is given to the design of the neural architecture, which is selected using a parsimonious and principled configuration intended to demonstrate feasibility rather than exhaustive optimisation.

By clarifying the scope, appropriate use cases, and practical boundaries of Deep SEM in an applied setting, this paper aims to serve as a practical reference for researchers interested in extending theory-driven SEM analyses with deep learning techniques, while remaining grounded in theory-driven model specification. Technical concepts are introduced alongside intuitive explanations to ensure accessibility for readers from diverse methodological backgrounds.

## Literature review

Structural Equation Modelling (SEM) has long been regarded as a cornerstone of quantitative research in behavioural and social sciences (Hair et al., 2021, 2022). It offers a unique ability to combine measurement models with structural models. While the measurement models capture the relationships between constructs and their observed indicators, structural models test hypothesised relationships among constructs (Gefen et al., 2000; Hair et al., 2021; Kline, 2016; Ulitzsch et al., 2023). This makes SEM particularly valuable for confirmatory theory testing, where researchers seek to validate conceptual frameworks. Over the past decades, SEM has contributed to advancing knowledge in areas ranging from psychology and education to business and information systems (Hair et al., 2019).

Beyond its methodological foundations, SEM has been widely applied across substantive research domains to investigate complex theoretical mechanisms involving latent variables. In psychology and education, SEM has been used to model cognitive processes, learning outcomes, motivation, and well-being, often incorporating mediation and moderation effects to test developmental and behavioural theories (Kline, 2023; Schamberger et al., 2025). In business and marketing research, SEM has been extensively employed to study consumer attitudes, brand loyalty, service quality, and decision-making processes, particularly within technology acceptance and adoption frameworks (Hair et al., 2019; Radhakrishna et al., 2024; Sarstedt et al., 2022). Similarly, in information systems and human-computer interaction research, SEM has become a dominant analytical approach for evaluating user experience, usability, and technology acceptance models, such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003), where latent psychological constructs play a central role (Cepeda et al., 2024; Gefen et al., 2000, 2003; Hair et al., 2021). These applications illustrate that SEM's enduring value lies not only in its statistical formalism, but also in its ability to operationalise theory-driven explanations of complex social and behavioural phenomena.

Within the broader SEM tradition, two major paradigms are commonly distinguished: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM, implemented in software such as *lavaan*, *Mplus*, and *LISREL*, is primarily theory-driven and aims to reproduce the observed covariance matrix under a set of hypothesised

measurement and structural relations (Bollen, 1989; Kline, 2016, 2023). It is most commonly used for confirmatory modelling, theory testing, and model comparison, with emphasis placed on global model fit and parameter estimation under well-specified measurement models (Hair et al., 2017, 2025; Vuković, 2024). Importantly, CB-SEM estimates measurement and structural model parameters simultaneously through a joint likelihood-based approach and does not explicitly produce latent variable scores. In contrast, PLS-SEM adopts a component-based estimation philosophy that prioritises explained variance and predictive accuracy, making it attractive for exploratory modelling, complex models with many indicators, and situations involving smaller samples or non-normal data (Hair et al., 2019, 2021; Sarstedt et al., 2022). In this approach, latent variable scores are first approximated through weighted composites of observed indicators and subsequently used to estimate structural relationships among constructs. Despite these differences, both paradigms rely on latent variable modelling as a core conceptual foundation, differing primarily in estimation objectives rather than in theoretical interpretation.

Yet, the very features that make SEM rigorous may also introduce practical constraints in certain research settings. Classical SEM approaches assume linearity, multivariate normality, and relatively large sample sizes (Schamberger et al., 2025; Ulitzsch et al., 2023), conditions that are not always met in practice. Moreover, while SEM excels at explaining variance and testing theoretical pathways, its predictive performance is often modest when compared to contemporary machine learning methods (Shmueli, 2010; Shmueli et al., 2016, 2019). This tension between explanation and prediction has sparked ongoing debates about how to expand SEM beyond its traditional confirmatory role.

Recent methodological work has highlighted conditions under which traditional SEM may face practical challenges. For example, Vowels (2024) shows that SEM's linearity assumptions can introduce bias under nonlinear relationships. Richter and Tudoran (2024) demonstrate that combining SEM with machine learning improves predictive accuracy. Irmer et al. (2024) note that nonlinear SEM models often require much larger sample sizes or advanced power estimation techniques. Similarly, Ulitzsch et al. (2023), in their comparison of maximum likelihood and alternative estimation methods (eg, Bayesian, constrained ML), report that SEM's performance declines under such constraints. Finally, Deng et al. (2018) provide a systematic review showing that SEM may fail when sample sizes are small or when the number of variables is high.

Parallel to SEM's development, deep learning has emerged as a powerful approach for uncovering patterns in complex, high-dimensional data (Mohd Noor and Ige, 2025). Deep neural networks (DNNs) can model nonlinear interactions, adapt to different data distributions, and achieve remarkable predictive accuracy across domains such as natural language processing, computer vision, and health analytics (Goodfellow

et al., 2016; LeCun et al., 2015; Lin et al., 2025). However, the strength of DNNs in prediction often comes at the expense of interpretability (Doshi-Velez and Kim, 2017; Li et al., 2022) – earning them the reputation of being “black boxes.” For researchers who prioritise theory testing, this opacity limits the direct adoption of deep learning in fields where causal interpretation is central.

Recently, a small but growing body of methodological research has explored ways of extending SEM to make it more compatible with contemporary predictive modelling techniques. For example, van Kesteren and Oberski (2022) reformulate SEM as a computational graph, enabling optimisation using tools developed in deep learning. Similarly, de Rooij et al. (2023) argue that SEM evaluation can be enriched by considering predictive criteria, such as out-of-sample performance, alongside traditional fit indices. Building on this emerging line of work, several studies have explored hybrid approaches that combine SEM with artificial neural networks, commonly referred to in the literature as SEM-ANN. This stream of research integrates latent variable modelling with neural network-based prediction to capture potential nonlinear relationships. More recently, related formulations – sometimes described as Neural SEM or Deep SEM – have been proposed, in which the structural relationships specified by SEM are modelled using deep neural networks while retaining the theory-driven causal structure. These approaches aim to extend SEM's explanatory capabilities with greater flexibility, while preserving its conceptual foundations. Importantly, these approaches are not intended to replace classical SEM, which remains highly effective and appropriate for the vast majority of applied research, but rather to explore complementary modelling options in settings where nonlinearities or predictive objectives are of particular interest (Richter and Tudoran, 2024; Yarkoni and Westfall, 2017).

Taken together, this literature reflects a cautious and exploratory shift towards viewing explanation and prediction as potentially complementary goals rather than competing paradigms. Deep SEM sits at this intersection as a specialised and still-developing extension of conventional SEM, one that remains grounded in latent variable modelling and theory-driven specification, while selectively incorporating neural components for enhanced flexibility. At present, such approaches occupy a niche methodological space and are most appropriately viewed as supplements to, rather than substitutes for, established SEM practices. This perspective provides the conceptual backdrop for the applied illustration presented in this study.

## Methodology

### *Baseline Structural Equation Modelling*

Structural Equation Modelling (SEM) provides a unified framework for specifying and estimating relationships among

latent variables through two interconnected components: (i) a *measurement model*, which defines how latent constructs are operationalised by observed indicators, and (ii) a *structural model*, which specifies the hypothesised directional relationships among these constructs. In applied research, SEM is most commonly estimated using covariance-based SEM (CB-SEM) or partial least squares SEM (PLS-SEM), depending on the research objective and data characteristics.

In this study, the baseline SEM was estimated using covariance-based SEM, implemented in R with the *lavaan* package (Rosseel, 2012; Rosseel et al., 2025). CB-SEM is particularly appropriate in theory-driven settings where the primary goal is to test well-specified measurement and structural models and to assess global model fit. Estimation followed standard practice, assuming linear relationships among constructs and relying on maximum likelihood estimation under conventional distributional assumptions (Kline, 2016, 2023).

The baseline SEM serves two purposes in this study. First, it provides a classical SEM benchmark against which subsequent analyses can be interpreted. Second, it yields latent variable scores derived from the estimated measurement model. While latent variables in SEM are theoretical entities rather than directly observed quantities, such factor scores are commonly used in applied settings as inputs for downstream analyses, including predictive modelling and hybrid SEM-machine learning workflows.

### Deep SEM framework

Building on the baseline SEM, this study adopts the Deep SEM framework as implemented in the *SEMdeep* R package (Grassi, 2025). Deep SEM does not replace classical SEM, but rather extends it by embedding flexible predictive components, such as deep neural networks or other machine learning algorithms, within a predefined SEM causal structure.

Conceptually, the Deep SEM approach preserves the theory-driven specification of latent constructs and their relationships, while allowing selected endogenous constructs to be modelled using nonlinear function approximators instead of linear regressions. In practical terms, this means that the structural paths associated with endogenous variables can be estimated using neural networks, thereby enabling the modelling of nonlinearities and interaction effects that are difficult to capture within traditional SEM.

Consistent with the design philosophy of *SEMdeep*, the workflow adopted in this study proceeds in two stages. First, a conventional CB-SEM model is estimated to validate the measurement structure and obtain latent variable scores. Second, these scores are used as inputs to the Deep SEM model, where neural components are introduced at the structural level. This stepwise strategy reflects established practice in hybrid SEM-machine learning research and allows predictive flexibility to be introduced without abandoning the interpretability and theoretical grounding of SEM.

Importantly, the use of Deep SEM in this study is illustrative rather than exhaustive. The neural architectures are specified in a parsimonious and transparent manner, with the aim of demonstrating feasibility, interpretability, and the overall modelling workflow, rather than maximising predictive performance through extensive hyperparameter optimisation or architectural tuning.

### Implementation using the *SEMdeep* package

All Deep SEM analyses in this study were conducted in R using the *SEMdeep* package (Grassi, 2025). *SEMdeep* provides an applied framework for embedding machine learning components within a predefined SEM structure, while maintaining a graph-based representation of latent variables and their relationships. The package builds on *SEMgraph* (Grassi et al., 2022) and *igraph* (Csardi and Nepusz, 2006) for model representation, and integrates *lavaan* for classical SEM estimation alongside modern deep learning backends such as *torch* (Falbel and Luraschi, 2025).

Conceptually, *SEMdeep* operates by taking a user-specified SEM graph – typically derived from a validated CB-SEM model – and allowing selected endogenous relationships to be modelled using nonlinear learners, including deep neural networks. This design enables researchers to retain the theory-driven structure of SEM while selectively introducing predictive flexibility at the structural level.

In the present study, *SEMdeep* is used to illustrate the core Deep SEM workflow rather than to exhaustively explore all available functionality. The package includes a set of key functions that support the estimation of hybrid SEM-deep learning models, model evaluation, interpretation, and visualisation. Table 1 provides an overview of selected core functions available in *SEMdeep* and their primary purposes, as described in the official documentation.

Importantly, not all functions listed in Table 1 are necessarily employed in the empirical illustration presented here. Their inclusion serves to clarify the scope of *SEMdeep*'s capabilities and to situate the applied analysis within the broader functionality of the package. Additional technical details and advanced options are beyond the scope of this applied tutorial and can be found in the *SEMdeep* Reference Manual (Grassi, 2025).

Within the *SEMdeep* framework, neural networks are employed as flexible function approximators in the structural model to capture potential nonlinear relationships among latent variables that cannot be represented by linear SEM paths. Neural networks are particularly suitable in this context due to their compatibility with the graph-based SEM representation and their ability to model complex functional forms.

In this study, the neural components were specified using a parsimonious feedforward architecture with three hidden layers, each comprising ten neurons, and the SELU activation function. This configuration reflects a deliberate balance

**Table 1.** Overview of selected core functions in the SEMdeep package.

| Function                                                                                                       | Use                                                                                                        |
|----------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|
| <code>SEMdnn()</code>                                                                                          | To estimate Deep SEM models with neural network-based structural components                                |
| <code>predict.SEM(), predict.DNN()</code>                                                                      | To generate predictions under classical SEM and Deep SEM specifications                                    |
| <code>getConnectionWeight(),</code><br><code>getGradientWeight(),</code><br><code>getSignificanceTest()</code> | To support interpretation and statistical assessment of neural inputs, and to enhance model explainability |
| <code>trainingReport()</code>                                                                                  | To monitor and visualise the neural network training process                                               |
| <code>crossValidation()</code>                                                                                 | To support model validation and performance assessment                                                     |
| <code>nplot(), mapGraph()</code>                                                                               | To visualise and modify the underlying graph-based model representation                                    |

Source: Authors' own compilation.

between expressive capacity and interpretability and is consistent with the tutorial-oriented objective of demonstrating the Deep SEM workflow rather than maximising predictive performance.

Model training was conducted using the *SEMdnn()* function with a moderate number of training epochs (1000) and a batch size of 64, which are sufficient for stable estimation in this illustrative setting. The training process was monitored using the *trainingReport()* function to ensure convergence and to provide transparency regarding the learning dynamics. Apart from these explicitly specified settings, all remaining parameters were retained at their documented default values. No extensive hyperparameter tuning was performed; accordingly, the reported Deep SEM results should be interpreted as illustrative of the method's operation rather than as optimised predictive benchmarks.

## Demonstration

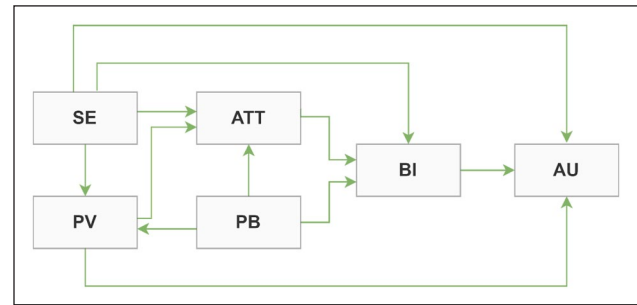
### Dataset and ethical considerations

To demonstrate the proposed SEM and Deep SEM workflow, this study relies on an empirical dataset originally reported by Kumi and Boateng (2024), which investigates cryptocurrency awareness, attitudes, and adoption intentions among tertiary institutions in Ghana. The dataset was collected using a structured survey instrument and is reused here solely for secondary analysis and methodological illustration.

The present study involves no new data collection. No personally identifiable information is included, and all analyses are conducted on anonymised and aggregated data. Accordingly, the current work does not introduce additional ethical considerations beyond those associated with the original data collection.

### Dataset description and preprocessing

From the original dataset, a sample of 750 complete observations, which represent students, was retained for analysis. The dataset comprises six latent constructs commonly used in technology adoption research: social effects (SE),

**Figure 1.** Conceptual framework of the study.

Source: Authors' own work.

perceived benefits (PB), perceived value (PV), attitude (ATT), behavioural intention (BI), and actual use (AU). Each construct is measured using three reflective indicators assessed on Likert-type scales.

Prior to model estimation, the data were screened for missing values and inconsistencies. Only complete cases were used in the analysis to ensure comparability across the traditional SEM and Deep SEM implementations.

### Conceptual model and substantive motivation

The conceptual model employed in this demonstration is grounded in established technology acceptance and adoption theories, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasise the roles of perceived benefits, attitudes, social influences, and behavioural intentions in shaping technology use (Davis, 1989; Venkatesh et al., 2003).

Figure 1 presents the conceptual framework guiding the analysis and illustrates the hypothesised relationships among the latent constructs. The framework reflects established adoption models in which social and cognitive factors shape attitudes and intentions, which in turn influence actual usage behaviour. In the present study, the conceptual model serves as a representative example for methodological demonstration rather than as a novel theoretical proposal.

In this framework, social effects (SE) and perceived benefits (PB) are hypothesised to influence perceived value (PV) and attitudes towards cryptocurrency (ATT), which in turn shape behavioural intention (BI) and actual use (AU). The dependent (endogenous) construct “actual use” refers to respondents’ self-reported engagement with cryptocurrency-related activities, such as ownership, transactions, or usage frequency, as operationalised in the original study by Kumi and Boateng (2024).

The model was selected because it reflects a well-established class of adoption models involving mediated relationships among latent psychological constructs, making it suitable for demonstrating both explanatory SEM estimation and predictive extensions using neural networks.

### Demonstration scope and analytical intent

Consistent with the pedagogical aim of this paper, the empirical analysis is designed to illustrate how conventional covariance-based SEM and Deep SEM can be applied to the same theoretical model under identical specifications. The goal is not to advance a new substantive theory of cryptocurrency adoption, but to provide a transparent comparison of explanatory and predictive modelling workflows using *SEMdeep*.

Accordingly, emphasis is placed on clarity of implementation, interpretability of results, and alignment with established SEM conventions, rather than on exhaustive model tuning or domain-specific hypothesis testing.

### R implementation workflow

We implemented the Deep SEM model in R using the *SEMdeep* package (version 1.1.1) within the RStudio environment. The analytical workflow followed five main steps:

1. Specification and estimation of the traditional SEM using covariance-based methods.
2. Construction of a directed graph object representing the SEM structure.
3. Extraction of latent variable (factor) scores from the fitted SEM.
4. Training of the Deep SEM model using the graph representation and extracted latent scores as inputs to the neural network components.
5. Reporting and interpretation of results from both the traditional SEM and Deep SEM specifications.

This stepwise procedure ensures consistency between the classical SEM and Deep SEM implementations, enabling a transparent comparison of explanatory and predictive modelling outputs. The full R code that supports the implementation of both the baseline SEM and Deep SEM is provided in the Supplemental Material.

**Table 2.** Fit indices of the Traditional SEM.

| Fit index | Value | Threshold (Hu and Bentler, 1999) |
|-----------|-------|----------------------------------|
| CFI       | 0.976 | $\geq 0.95$                      |
| TLI       | 0.970 | $\geq 0.95$                      |
| RMSEA     | 0.048 | $\leq 0.06$                      |
| SRMR      | 0.029 | $\leq 0.08$                      |
| NFI       | 0.963 | $\geq 0.90$                      |

Source: Authors’ own compilation.

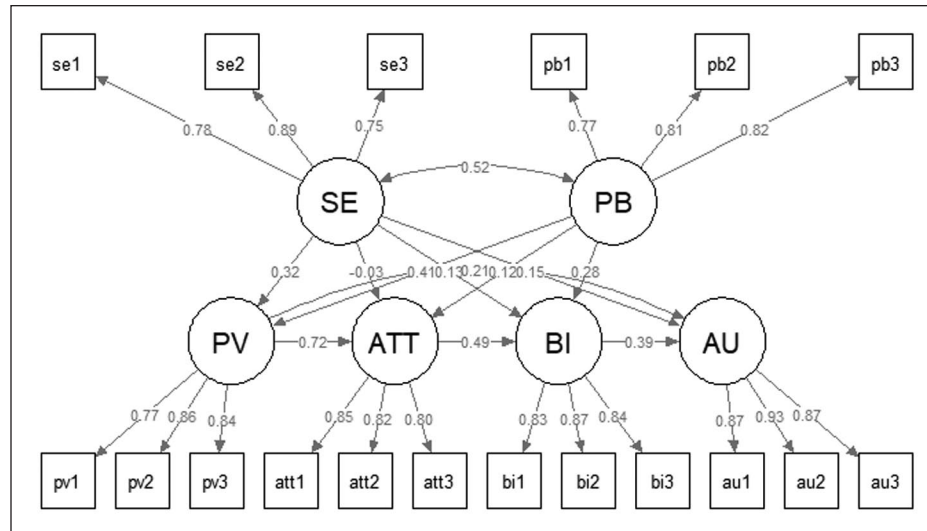
## Results

### SEM

The traditional SEM model demonstrated an excellent fit to the data based on established thresholds by Hu and Bentler (1999), as depicted in Table 2. All incremental fit indices exceeded recommended cutoffs (CFI=0.976, TLI=0.970, NFI=0.963), while absolute fit indices indicated good model adequacy (RMSEA=0.048, SRMR=0.029). These results confirm that the specified SEM appropriately represents the underlying theoretical relationships among the constructs. Figure 2 shows the measurement and structural models of the SEM model. The indicator loadings for all constructs exceeded the recommended threshold of 0.708 (Cepeda et al., 2024; Hair et al., 2021; Ringle et al., 2023), indicating that each item explained more than 50% of the variance of its corresponding construct. All but one of the eleven hypothesised structural paths were statistically significant and aligned with the proposed directions, as presented in Table 3. Social effects (SE;  $\beta=0.323$ ,  $p<0.001$ ) and perceived benefits (PB;  $\beta=0.407$ ,  $p<0.001$ ) both had significant positive effects on perceived value (PV). Similarly, perceived benefits ( $\beta=0.118$ ,  $p=0.006$ ) and perceived value ( $\beta=0.722$ ,  $p<0.001$ ) positively predicted attitude (ATT), whereas SE ( $\beta=-0.031$ ,  $p=0.455$ ) showed no significant effect, resulting in the rejection of the directional path (hypothesis). Furthermore, behavioural intention (BI) was positively influenced by ATT ( $\beta=0.489$ ,  $p<0.001$ ), PB ( $\beta=0.281$ ,  $p<0.001$ ), and SE ( $\beta=0.128$ ,  $p=0.001$ ). Finally, BI ( $\beta=0.386$ ,  $p<0.001$ ), PV ( $\beta=0.206$ ,  $p<0.001$ ), and SE ( $\beta=0.150$ ,  $p<0.001$ ), all significantly predicted actual use (AU). These results are consistent with prior studies on technology adoption (Acquah et al., 2024; Durak and Onan, 2024; Saihi et al., 2025; Salifu et al., 2024; Wiangkham and Vongvit, 2024), including recent research on digital and cryptocurrency adoption (Amin et al., 2025; Çalışkan and Turan, 2025). Collectively, the model accounted for 40.7% of the variance in PV ( $R^2=0.407$ ), 60.8% in ATT ( $R^2=0.608$ ), 56.7% in BI ( $R^2=0.567$ ), and 39.9% in AU ( $R^2=0.399$ ).

### Deep SEM

Table 4 reports the path-specific connection weights obtained from the Deep SEM model estimated using the *SEMdnn()*



**Figure 2.** Measurement and structural models.

Source: Plotted in R using semPlot package; Epskamp (2025).

**Table 3.** Traditional SEM path estimates.

| Path   | $\beta$ | $R^2$ | SE    | z      | p-value | CI lower | CI upper | Decision  |
|--------|---------|-------|-------|--------|---------|----------|----------|-----------|
| SE→PV  | 0.323   | 0.407 | 0.042 | 7.771  | <0.001  | 0.242    | 0.405    | Supported |
| PB→PV  | 0.407   | 0.407 | 0.041 | 9.890  | <0.001  | 0.327    | 0.488    | Supported |
| SE→ATT | -0.031  | 0.608 | 0.041 | -0.747 | 0.455   | -0.111   | 0.050    | Rejected  |
| PB→ATT | 0.118   | 0.608 | 0.043 | 2.725  | 0.006   | 0.033    | 0.204    | Supported |
| PV→ATT | 0.722   | 0.608 | 0.037 | 19.274 | <0.001  | 0.649    | 0.796    | Supported |
| ATT→BI | 0.489   | 0.567 | 0.036 | 13.693 | <0.001  | 0.419    | 0.559    | Supported |
| PB→BI  | 0.281   | 0.567 | 0.042 | 6.725  | <0.001  | 0.199    | 0.363    | Supported |
| SE→BI  | 0.128   | 0.567 | 0.038 | 3.322  | 0.001   | 0.052    | 0.203    | Supported |
| BI→AU  | 0.386   | 0.399 | 0.044 | 8.853  | <0.001  | 0.301    | 0.472    | Supported |
| PV→AU  | 0.206   | 0.399 | 0.047 | 4.337  | <0.001  | 0.113    | 0.298    | Supported |
| SE→AU  | 0.150   | 0.399 | 0.042 | 3.591  | <0.001  | 0.068    | 0.232    | Supported |

Source: Authors' own compilation.

Note.  $\beta$ : path coefficient;  $R^2$ : coefficient of determination; SE: standard error; z: statistic test; CI: confidence interval.

function. In line with the current *SEMdeep* framework, variable contributions for Deep SEM are assessed using training-based measures, rather than testing-based metrics. In particular, connection weights, commonly used in the SEM-ANN literature as a measure of relative variable importance – are employed to evaluate the contribution of structural paths within the nonlinear model.

The raw connection weights reflect the strength and direction of relationships learned by the neural network components. To facilitate comparison across paths, these values are transformed into normalised connection weights by scaling the absolute weights relative to their total sum. The resulting values are non-negative and sum to one, thereby providing a proportional measure of each structural path's contribution within the overall network. Importantly, these normalised weights do not represent explained variance, but instead

quantify the relative influence of each path within the fitted Deep SEM model.

As shown in Table 4 and Figure 3, the largest contributions are observed for the paths PB→BI (0.141), PB→PV (0.138), and PV→ATT (0.137), followed by SE→AU (0.105) and BI→AU (0.102). These results highlight the prominent role of perceived benefits and perceived value in shaping both intermediate cognitive evaluations and downstream behavioural outcomes. In particular, the strong contribution of the path PV→ATT reinforces the mediating role of perceived value in influencing attitudes, which subsequently drive behavioural intention and actual use.

Taken together, these results highlight the central mediating roles of perceived value, attitude, and behavioural intention in shaping cryptocurrency adoption, consistent with behavioural adoption theory. Prior research similarly

**Table 4.** Path-specific normalised connection weights from the Deep SEM model.

| Path   | Raw weight | Normalised weight |
|--------|------------|-------------------|
| SE→PV  | 3.198      | 0.083             |
| PB→PV  | 5.312      | 0.138             |
| SE→ATT | -0.742     | 0.019             |
| PB→ATT | 1.245      | 0.032             |
| PV→ATT | 5.280      | 0.137             |
| ATT→BI | 3.790      | 0.098             |
| PB→BI  | 5.428      | 0.141             |
| SE→BI  | 3.163      | 0.082             |
| BI→AU  | 3.922      | 0.102             |
| PV→AU  | 2.477      | 0.064             |
| SE→AU  | 4.067      | 0.105             |

Source: Authors' own compilation.

Note. Raw weights are obtained from the trained neural network, while normalised weights represent the relative contribution of each path based on the absolute sum of connection weights.

emphasises the importance of perceived value (Abdurrahman et al., 2026; García-Monleón et al., 2023) and attitude (Arpaci and Bahari, 2023; Cristofaro et al., 2023) as key mechanisms influencing behavioural intention and actual use.

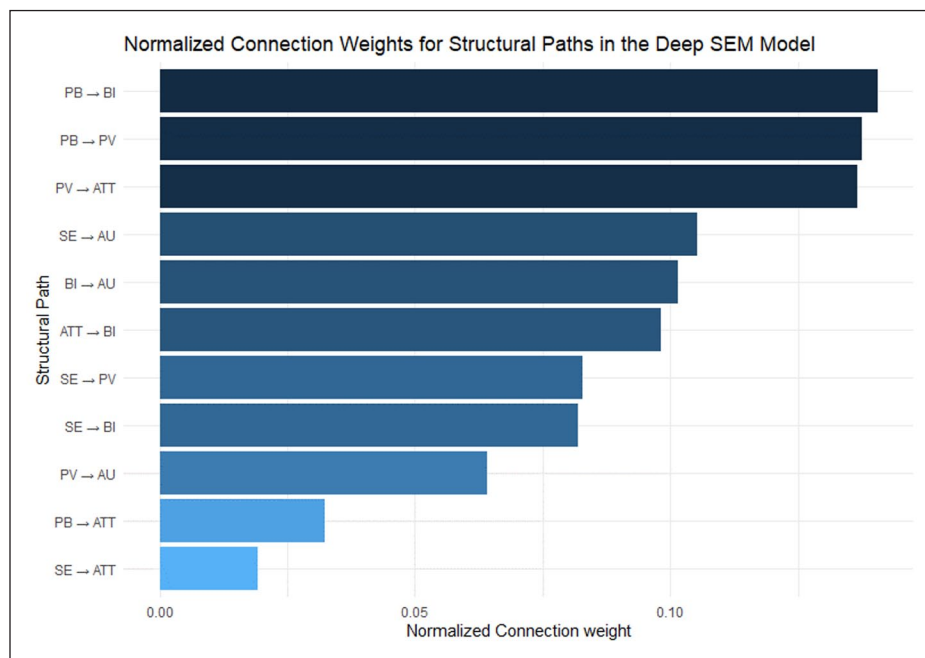
Moderate contributions are observed for ATT→BI (0.098), SE→PV (0.083), and SE→BI (0.082), suggesting that social influence exerts a supporting role within the adoption process. In contrast, relatively small contributions are associated with PV→AU (0.064), PB→ATT (0.032), and

SE→ATT (0.019), indicating that these relationships play a more limited role within the nonlinear model. Notably, the weak contribution of SE→ATT is consistent with the corresponding path in the traditional SEM analysis, where it was found to be statistically non-significant. This convergence suggests that the limited role of social influence in shaping attitudes is robust across both linear and nonlinear specifications.

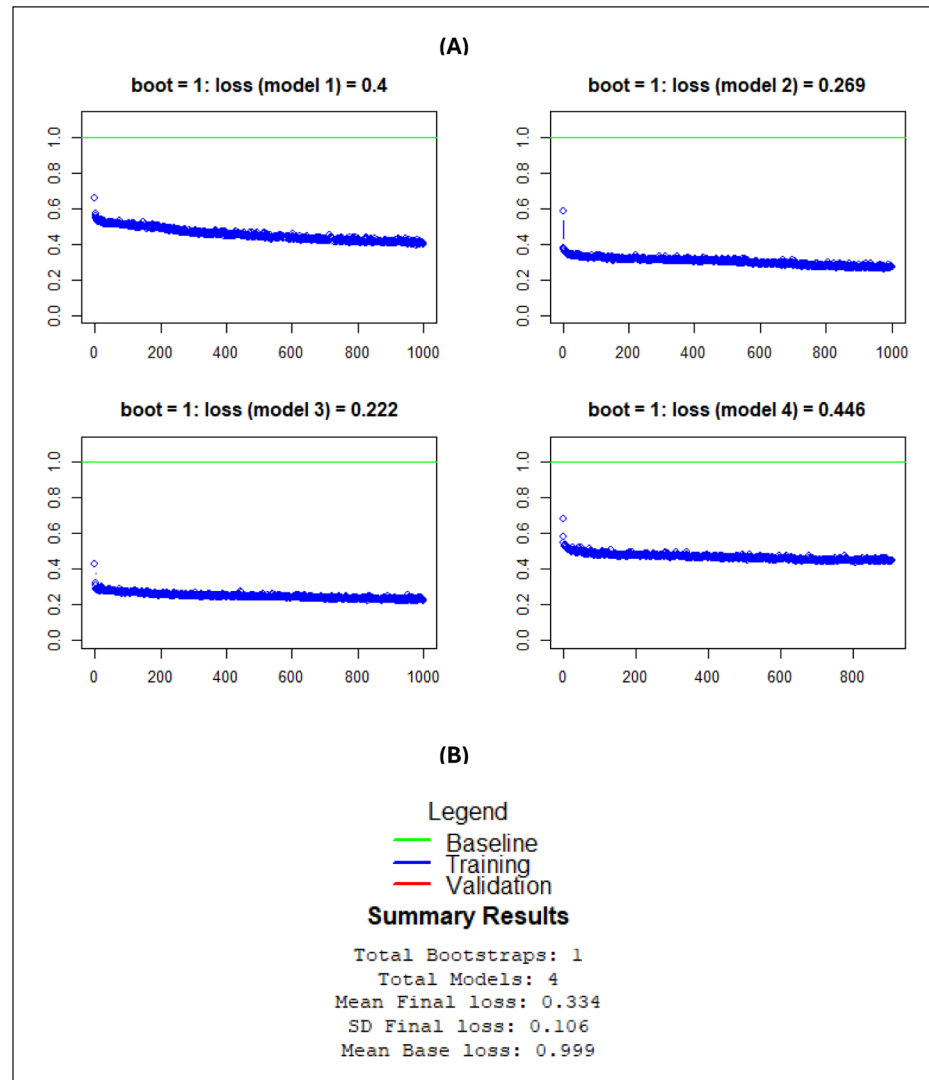
Overall, the Deep SEM results preserve the theoretically meaningful mediation structure identified in the baseline SEM, while providing additional insight into the relative contribution of structural paths under a flexible nonlinear estimation framework. Figure 3 visualises these normalised connection weights, providing an intuitive comparison of the strength of relationships across the model.

Figure 4 presents the training dynamics of the Deep SEM model. Panel A illustrates the evolution of training loss across epochs for each endogenous construct, showing a consistent decline and stabilisation, which indicates satisfactory model convergence. Panel B summarises the overall training performance, including mean final loss and baseline loss. No validation loss is reported, as no validation split was specified (validation=0), consistent with the tutorial-oriented and in-sample focus of the analysis.

Table 5 compares the proportion of explained variance ( $R^2$ ) for endogenous constructs obtained from the traditional covariance-based SEM and the Deep SEM specification. Across all constructs, Deep SEM yields higher  $R^2$  values, with improvements observed for perceived value ( $\Delta R^2 = +0.156$ ), attitude

**Figure 3.** Normalised connection weights illustrating the relative contribution of structural paths in the Deep SEM model.

Source: Plotted in R using ggplot2 package; Wickham (2016).



**Figure 4.** Training dynamics of the Deep SEM model: (a) Training loss trajectories across epochs for each endogenous model estimated within the SEMdeep framework and (b) summary statistics of the training process, including mean final loss and baseline loss.

Note. Validation loss is not shown, as no validation split was specified (validation=0), consistent with the illustrative and in-sample focus of the analysis.

**Table 5.** Comparison of traditional SEM and Deep SEM.

| Construct | $R^2$ (SEM) | $R^2$ (Deep SEM) | $\Delta R^2$ (Deep SEM–SEM) |
|-----------|-------------|------------------|-----------------------------|
| PV        | 0.407       | 0.563            | +0.156                      |
| ATT       | 0.608       | 0.779            | +0.171                      |
| BI        | 0.567       | 0.733            | +0.166                      |
| AU        | 0.399       | 0.612            | +0.213                      |

Source: Authors' own compilation.

( $\Delta R^2 = +0.171$ ), behavioural intention ( $\Delta R^2 = +0.166$ ), and actual use ( $\Delta R^2 = +0.213$ ). These results suggest that the non-linear components capture additional variance beyond that explained by linear structural relationships.

However, these improvements should be interpreted with caution. The reported  $R^2$  values reflect in-sample explanatory performance, as no data partitioning or cross-validation

procedure was applied. Given the flexibility of neural networks, improved fit to the training data may reflect increased model flexibility rather than superior out-of-sample predictive performance. Accordingly, the results should be viewed as illustrative of the potential of Deep SEM, rather than as definitive evidence of improved generalisation.

Taken together, the findings indicate that Deep SEM can complement traditional SEM by preserving theory-driven structure while offering a more flexible representation of relationships among latent variables. At the same time, the consistency of the dominant pathways across both approaches reinforces the robustness of the underlying theoretical model.

## Discussion

This study contributes to ongoing methodological innovation in structural equation modelling by providing a transparent

and applied illustration of how deep learning components can be integrated into a theory-driven SEM framework using the *SEMdeep* package in R. Building on recent debates concerning explanation versus prediction in SEM (Shmueli, 2010; Shmueli et al., 2016, 2019; Yarkoni and Westfall, 2017), the analysis demonstrates how conventional covariance-based SEM and Deep SEM specifications can be implemented and interpreted within a unified workflow, thereby clarifying their respective roles and complementarities.

The traditional SEM exhibited strong explanatory performance and satisfactory global fit, consistent with its primary purpose of testing theoretically grounded relationships among latent constructs (Bollen, 1989; Kline, 2016, 2023). The pattern of significant and non-significant paths aligned closely with established technology adoption theories, reinforcing the adequacy of linear SEM for confirmatory analysis. In particular, perceived value, attitude, and behavioural intention emerged as central mediating mechanisms, while social effects showed a limited and non-significant influence on attitudes, a finding that is theoretically plausible and robust across modelling approaches (Davis, 1989; Venkatesh et al., 2003).

When the same structural model was estimated using the Deep SEM formulation, higher levels of explained variance were observed for all endogenous constructs. These gains should not be interpreted as evidence of superior causal identification, but rather as an indication that the neural components were able to capture additional variance under a more flexible functional form. Importantly, the dominant pathways identified by the Deep SEM model remained consistent with those estimated in the traditional SEM, suggesting that the integration of deep learning did not distort the underlying theoretical structure, but instead provided a complementary representation capable of accommodating potential nonlinearities (Richter and Tudoran, 2024).

The use of training-based variable contribution measures, specifically connection weights, further supports this interpretation. These measures do not replace SEM path coefficients or hypothesis testing, but instead provide additional insight into the relative contribution of structural paths within a nonlinear estimation framework. In this sense, Deep SEM extends the analytical toolbox available to SEM researchers by enabling exploratory assessment of functional complexity while remaining anchored in latent variable modelling.

Several limitations nonetheless merit attention. The Deep SEM results reported in this study are based on in-sample estimation, as the dataset was not partitioned into training and test subsets and no cross-validation procedure was applied. Consequently, improvements in explained variance should be interpreted as illustrative rather than as estimates of out-of-sample predictive generalisation. Moreover, neural network performance is sensitive to architectural choices and training strategies, and more systematic tuning or validation would be required in applied settings where prediction is the

primary analytical objective (Goodfellow et al., 2016; LeCun et al., 2015; Lin et al., 2025).

Taken together, these findings support a cautious and balanced view of Deep SEM as a methodological extension rather than a replacement of classical SEM. Covariance-based SEM remains highly effective for theory testing and causal hypothesis evaluation, which continues to be the dominant and appropriate use case in most applied research. Deep SEM occupies a more specialised methodological space, offering a complementary option for researchers who wish to explore whether nonlinear functional forms enhance explanatory or predictive performance under a theoretically specified model. Within this scope, the present study contributes to Methodological Innovations by clarifying the practical implementation, interpretation, and limitations of SEM-deep learning integration in applied research contexts.

## Conclusion

This study has demonstrated how Deep SEM can be used as a complementary extension to traditional structural equation modelling, offering additional flexibility for capturing nonlinear and interactive relationships while preserving the theory-driven structure that underpins SEM. By integrating latent variable modelling with neural network components, Deep SEM provides a unified framework in which explanation and prediction can be examined side by side, rather than treated as competing analytical objectives.

Using the *SEMdeep* package in R, the paper illustrated that Deep SEM workflows are practically feasible within familiar SEM-oriented environments. The implementation emphasised transparency and parsimony, focussing on a minimal neural architecture designed to demonstrate the modelling process rather than to maximise predictive performance through extensive tuning. Under this illustrative configuration, Deep SEM achieved higher in-sample explained variance than the corresponding covariance-based SEM, while maintaining consistency in the dominant structural pathways identified by theory.

Importantly, the results reinforce the view that improvements in predictive capacity should be interpreted as methodological complements rather than as evidence of superior causal validity. Traditional SEM remains well suited for confirmatory hypothesis testing and theory evaluation, whereas Deep SEM occupies a more exploratory and predictive role by allowing researchers to assess whether nonlinear functional forms provide additional explanatory insight under an explicitly specified theoretical model. The use of training-based variable contribution measures, specifically connection weights, further supports this integrative perspective by providing interpretable indicators of relative path contribution within a nonlinear estimation framework.

Overall, the contribution of this paper lies in clarifying the role, implementation, and interpretation of Deep SEM within applied research, rather than in proposing a replacement for

established SEM methodology. By demonstrating how deep learning can be incorporated into SEM in a transparent and theoretically grounded manner, the study contributes to ongoing methodological innovation in the field and provides practical guidance for researchers interested in extending SEM beyond linear assumptions.

Future research may build on this foundation by incorporating cross-validation and out-of-sample evaluation to more rigorously assess predictive generalisation and mitigate potential overfitting associated with flexible neural architectures. It may also explore alternative neural architectures and develop joint estimation procedures for measurement and structural components. Such developments would further strengthen the methodological toolkit available for analysing complex, data-rich phenomena in domains such as technology adoption, health informatics, and climate research, where both theoretical coherence and predictive insight are increasingly important.

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## ORCID iDs

Isaac Osei  <https://orcid.org/0009-0008-0159-4206>

Dennis Opoku Boadu  <https://orcid.org/0009-0005-8220-4086>

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## Data availability statement

The data analysed in this study are available via Zenodo at <https://doi.org/10.5281/zenodo.18441376>. The complete raw dataset is publicly accessible through Mendeley Data.

## Supplemental material

Supplemental material for this article is available online.

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## Author biographies

**Isaac Osei** is a Computer and Data Scientist with more than 12 years of experience in the IT industry and academia. He earned his Bachelor's degree in Computer Science from the University of Ghana, Legon, and later completed a Master of Computer Applications at Amity University, Noida, India. He is currently pursuing his PhD at SRM University-AP, India. His research interests span the application of Structural Equation Modelling (SEM) in Human-Computer Interaction (HCI) and Financial Technology, as well as Machine Learning, Deep Learning, Bioinformatics, and Applied Statistics.

**Chettupally Anil Carie** is a Computer Scientist and academic with extensive experience in teaching and research. He earned his Bachelor's degree in Computer Science and Engineering from Ramappa Engineering College, JNTU Hyderabad, and went on to

complete his Master of Technology at Karunya University of Technology, Coimbatore. He later received his PhD from Dalian University of Technology, China. He is currently an Associate Professor in the Department of Computer Science and Engineering at SRM University-AP, India. His research interests span Application of Structural Equation Modelling in Information Systems, Intelligent Internet of Things (IoT), vehicular and smart-city IoT systems, Deep Learning, advanced routing and resource-allocation algorithms, and network optimization for socially impactful applications.

**Bhaskar Marapelli** is an Associate Professor in the Department of Computer Science and Information Technology at KLEF (Deemed to be University), Vijayawada, India. He holds a Ph.D. in Computer Science and Engineering from Shri Jagadishprasad Jhabarmal Tibrewala University, Rajasthan. With over 17 years of academic and research experience, his interests include Software Engineering, Artificial Intelligence, and Machine Learning. Dr. Marapelli has authored and co-authored several research papers in reputed Scopus-indexed journals and IEEE conferences. He has also served as the Principal Investigator for consultancy and sponsored research projects in the areas of AI-driven automation and educational data security. His recent research focuses on Explainable AI (XAI) and the application of machine learning techniques for software effort estimation and healthcare diagnostics.

**Dennis Opoku Boadu** is a Computer Science Lecturer and Researcher at the University of Ghana and Ghana Christian University College. He holds an MPhil in Computer Science from the Kwame Nkrumah University of Science and Technology, an M.A in Development Communication at Ghana Institute of Journalism, a BSc in Computer Science at the University of Ghana, Legon and also a PhD Candidate in Computer Science at the University of Ghana. His research spans machine learning, graph-based computational models, and virtual reality applications in the fields of health and education. He explores how AI, bioinformatics, and blockchain security can drive innovation and social transformation. Dennis has published and reviewed several works in journals such as Operations Research Forum, IGI Global, and PLOS. Passionate about mentoring and system design, he combines academic rigour with practical implementation to bridge data science, technology, and human development.

**Satish Anamalamudi** received the B.Eng. degree in Computer Science and Engineering from JNTU Hyderabad, the M.Tech. degree from Karunya University, and the Ph.D. degree in Communication and Information Systems from the Dalian University of Technology, China. He has professional experience as a Research Engineer at Huawei Technologies, Beijing. Currently, he is an Associate Professor at SRM University-AP, India, where he also serves as Director (I/C) – ITKM. His research focuses on MAC and routing protocols for cognitive radio ad hoc networks, IoT, and 5G systems.