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ORIGINAL RESEARCH

Investigating Key Factors Influencing Students' Acceptance and Satisfaction with a Block Model E-Learning System: An Integrated SEM-Neural Network Approach

Golam Sorwar[1] · Reza Ghanbarzadeh[1] · Jenelle Benson[1] · Raina Mason[1] · Md. Yahin Hossain[2]

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Abstract
Intensive or Block models, along with e-learning, have become a vital element in the transformation of higher education, leveraging technological advancement and the necessity for flexible, student-centred learning. Although research investigating students' acceptance and adoption of traditional semester-based e-learning is well-established, systematic empirical investigation of key factors for students' perception of, engagement with and satisfaction with E-learning Block Models (EBMs) remains limited in higher education. The study developed a theoretical model based on information systems success and the technology acceptance model called Evaluating E-learning Systems Success (EESS), with additional factors for the block model aspect: social norms and self-regulatory learning. Data was collected from 974 undergraduate and postgraduate students across diverse disciplines of study in a regional university and analysed using two steps: structural equation modelling and artificial neural networks, to examine the relationships between variables and the relative importance of each factor for the benefits of EBMs. The findings reveal that system quality, information quality, and service quality significantly influence students' perceived usefulness and actual use of the EBM system. Perceived usefulness, in turn, has a significant positive effect on user satisfaction with the EBM system. These perceptions drive system use and benefits, reinforcing EBM's success. Additionally, the study identifies social norms and self-regulatory learning as essential influences on student behaviour, further contributing to the effectiveness of the EBMs environment. This research offers valuable insights into the multifaceted dimensions of EBM success and provides practical implications for universities aiming to enhance student engagement, satisfaction, and learning outcomes by introducing block model teaching and learning in digital education environments.

Keywords Higher education · E-learning · System success · E-learning block models

Extended author information available on the last page of the article

Table 1 SCM overview of student schedule

Schedule	6 × 6-week term
	Up to 2 courses at one time
Delivery	A 1-h online workshop for all students
	2-h tutorials online or on-campus
Content	Content is developed in online modules using multimedia, videos, and active learning.



Fig. 1 The SCM yearly schedule. *Note*: Students do not need to attend in every term. They can enroll in 4 terms and take two courses each term to be considered full-time students

1 Introduction

Several universities have introduced innovative immersive delivery models, also known as "block" or "accelerated" models (Roche et al., 2024). Evidence from Loton et al. (2022) demonstrated that using intensive E-learning Block Models (EBM) increased students' success and satisfaction for equity groups. Southern Cross University (SCU) is no exception and, in 2021, adopted a modified EBM to improve student success. Southern Cross University is a regional Australian university that has a higher-than-average First Nations student population, along with a larger mature age student population (Trimble, 2023). The average SCU student age is between 20 and 29 years old (Trimble, 2023). Rural and remote universities typically attract students who attend through online study and students are more likely to be mature-aged, female, from lower socio-economic backgrounds, and enrolled part-time or online (Stoodley et al., 2016; Crawford & Emery, 2021; Ragusa & Steinke, 2012). This presents a unique population that has not been well-studied in the context of innovative delivery models. Regional students often experience additional barriers and require specific institutional support (Crawford & Emery, 2021; Stoodley et al., 2016). Regional students also have a higher rate of attending on a part-time basis to continue working (Trimble, 2023). All these unique factors require additional support services to be available within SCU in order to support students and improve their success. The EBM at SCU has been named the Southern Cross Model (SCM). Within the SCM, all students receive their content in the online classroom and via the online content, and practical activities such as workshops and tutorials are scheduled either on-campus or online (Roche et al., 2022). Table 1 shows the layout of the SCM.

In the SCM, the schedule has 6 terms per year, with each term having six weeks of teaching. The two or three weeks between terms are used for final grading and preparation for the next term for staff and a needed break for students (see Fig. 1 below) (Roche et al., 2022).

The SCM creates an online cohort for all students, whether on-campus or online, to attend the 1-h workshop, and then the students are moved into 2-h tutorials for either online or on-campus cohorts to facilitate group work and easier teacher/student interactions during the week (Goode et al., 2022a, 2022b). Each course is typically broken into six standardised modules—one to be studied each week. Each module has a clear progression of readings, activities and self-check materials, delivered via a Blackboard LMS learning site (Goode et al., 2022a, 2022b; Roche et al., 2022). Online content uses interactive H5P packages[1] to encourage active learning. Open Educational Resource (OER) texts or low-cost texts are used, when necessary, to increase accessibility to materials for students from low socio-economic backgrounds (Goode et al., 2022a, 2022b). Constructive alignment is used to align course learning outcomes with content and assessment tasks, with all extraneous concepts being removed or clearly placed in an optional study area to reduce cognitive load for novices. In this way, specified learning content is directly aligned with assigned assessment tasks and activities. These changes have increased the success rate of students since the model was deployed (Goode et al., 2023); but have not increased enrolments or student satisfaction. Understanding the factors influencing student satisfaction with the block model will provide important insights into improving the student experience alongside the observed improvements in student success.

Understanding adoption behaviour is important for any EBM's success. While extensive research exists in traditional and mobile learning, little has been done to explore factors influencing students' acceptance and adoption of EBMs, especially in higher education. Thomas et al. (2025) highlighted the benefits and challenges of intensive delivery modes but did not focus on student perspectives. Key areas affecting student success and satisfaction in intensive EBMs include learning engagement, materials, tutorials, workshops, and support and interactions from teachers and peers (Kwan et al., 2022). However, the referenced study was limited to a specific certificate course with 168 participants, mostly postgraduates, and lacked hybrid settings, limiting the generalisability of findings. Other critical factors, such as self-regulatory learning styles, technological issues, and social norms, may provide a more comprehensive understanding of satisfaction drivers. Goode et al., (2022a, 2022b) and Goode et al., (2022a, 2022b) examined the impact of student engagement with online content on academic success using retrospective data from the SCU Learning Management System (LMS). They focused on content design aspects, such as interactivity, media richness, constructive alignment, flexibility, and responsiveness. These studies found a significant correlation between behavioural engagement and student performance. However, engagement alone may not ensure academic success for example, Broadbent (2016); Goode et al., (2022a, 2022b). A broader range of factors, including psychological and motivational aspects like self-efficacy, motivation, perceived usefulness, ease of use, enjoyment, and institutional support, are crucial for understanding students' attitudes towards the SCM, its acceptance, and their satisfaction and success. Previous studies, such as Broadbent (2016), indicated that LMS activity might not predict academic success behaviours. Goode et al., (2022a, 2022b) also suggested that diverse samples are necessary for more generalised out-

[1] H5P (HTML5 Package) is a free, open-source framework that allows users to easily create, share, and reuse interactive HTML5 content—such as quizzes, interactive videos, presentations, and games—directly in a web browser without needing coding skills. It is designed for educators and content creators to boost engagement, integrating seamlessly with major platforms like Moodle, Canvas, and WordPress (h5p.org).

comes. While student success appears positive at a macroscopic level, few studies examine this aspect at a micro level in block models.

This study aims to address the above limitations by identifying key predictors affecting students' acceptance, adoption, satisfaction, and success with the new model. A theoretical framework was developed based on the Holsapple and Lee-Post e-Learning Success Model (Holsapple & Lee-Post, 2006), integrating other models and feedback from the SCU LMS. Data were collected via an online survey from various disciplines and study levels using purposive sampling. Structural equation modelling (SEM) will be used to analyse the data and test hypotheses about relationships among predictors and outcomes. The study's results will contribute to information systems and education research and provide practical insights for university academic leadership and management to develop effective immersive EBMs. The study will address the research question:

RQ: "*What are the key factors that influence students' acceptance and satisfaction when universities deliver educational content online using a block model?*".

2 Theoretical Framework and Hypothesis Development

This study adopts the multi-dimensional E-Learning Systems Success (EESS) model developed by Al-Fraihat et al. (2020) to evaluate e-learning success through system, information, and service quality, alongside user satisfaction. The EESS model integrates four key theoretical foundations: the DeLone and McLean Information Systems Success Model (D&M), the Technology Acceptance Model (TAM), user satisfaction theories, and domain-specific e-learning quality frameworks (Al-Fraihat et al., 2019). By combining technical, acceptance, pedagogical, and outcome-oriented constructs into a unified causal framework, the model addresses limitations of single-theory approaches and offers a comprehensive perspective on e-learning success.

The D&M model provides the primary structural foundation of EESS, conceptualising information system success as a process in which system, information, and service quality influence use and user satisfaction, which in turn determine net benefits (DeLone & McLean, 2003; Sabeh et al., 2021). While widely applied in e-learning research, the D&M model was not originally designed for educational contexts, necessitating extensions to capture pedagogical and learner-centred factors (Al-Fraihat et al., 2019, 2020; Holsapple & Lee-Post, 2006). These limitations motivated the integration of complementary theoretical perspectives within the EESS framework.

TAM contributes a user-centred perspective by emphasising perceived usefulness and perceived ease of use as key determinants of technology adoption (Lin & Chen, 2012). Within EESS, perceived usefulness is incorporated as a central mediator between quality dimensions, system use, and benefits, highlighting the role of learner acceptance in achieving e-learning success (Al-Fraihat et al., 2019, 2020). Although TAM's integration in EESS prioritises perceived usefulness over ease of use, it strengthens the model's ability to explain behavioural intentions and system engagement.

User satisfaction constitutes the third theoretical pillar of EESS and functions as a critical mediating variable between quality antecedents and outcomes. Satisfaction reflects users' overall evaluation of their learning experience and influences both continued system use and perceived benefits (Shee & Wang, 2006). While treated as a unidimensional construct

in EESS, satisfaction remains a widely validated indicator of e-learning success. The fourth foundation comprises e-learning quality models that emphasise pedagogical and human factors, including educational system quality, instructor quality, learner quality, and support system quality (Al-Fraihat et al., 2019, 2020; Holsapple & Lee-Post, 2006). These constructs extend traditional IS success models by capturing educational dimensions critical to learning effectiveness.

Collectively, the EESS model operationalises these four foundations into 11 constructs organised in a process-oriented causal sequence: seven quality antecedents, two mediators (perceived satisfaction and perceived usefulness), and two outcomes (system use and benefits). Empirical studies across diverse contexts have validated the model's robustness and adaptability, demonstrating that different quality dimensions vary in importance depending on educational settings and conditions (Nawanda & Tambotoh, 2024; Ouajdouni et al., 2022). This adaptability makes the model well-suited for innovative teaching models such as EBMs, which enhance student engagement and academic success in immersive learning environments (Goode et al., 2022a, 2022b).

Recognising the evolving demands of modern educational environments, this study makes its contribution to literature by extending the original model by incorporating two additional constructs, social norms and self-regulatory learning. Self-regulatory learning has been incorporated into extensions of technology-acceptance frameworks but is not included in the original EESS model. This critical construct will be reintroduced into the conceptual model for this research project. Social norms, defined as the expectations and behaviours learners perceive and learn from peers and instructors, significantly influence students' adoption and sustained use of e-learning systems. Research has shown that social norms profoundly impact learners' attitudes towards technology, including satisfaction and their engagement with online learning platforms (Günther, 2021).

The inclusion of self-regulatory learning acknowledges the importance of fostering student autonomy and self-direction within e-learning environments. Self-regulatory strategies, such as goal setting, self-monitoring, and time management, have been identified as key drivers of academic success in e-learning settings, especially for interactive EBMs. Yavuzalp and Bahcivan (2021) demonstrated that self-regulation skills positively correlate with students' satisfaction and academic achievement in e-learning environments. Kumar (2022) also emphasised that self-regulatory learning enhances motivation and engagement in executive education programs.

By extending the model with these two constructs, this study provides a more comprehensive and robust framework for evaluating students' adoption, satisfaction and learning success in EBMs. This integrated approach offers a robust framework for understanding the diverse factors that influence student engagement, satisfaction, and learning outcomes, making it particularly well-suited for evaluating contemporary EBMs. Theoretically, this inclusion is grounded in Zimmerman's (1990, 2002) social cognitive model of self-regulatory learning, which characterises effective learning as a cyclical process comprising forethought (goal setting, strategic planning), performance (self-monitoring, task strategy use), and self-reflection (self-evaluation, adaptive response). These processes are proactively initiated by the learner rather than externally directed, making them particularly applicable to the SCM's intensive, modular structure, where students must independently navigate compressed six-week terms and online content without the scaffolding of a traditional semester rhythm (Panadero & Alonso-Tapia, 2014). Figure 2 presents the proposed conceptual model.

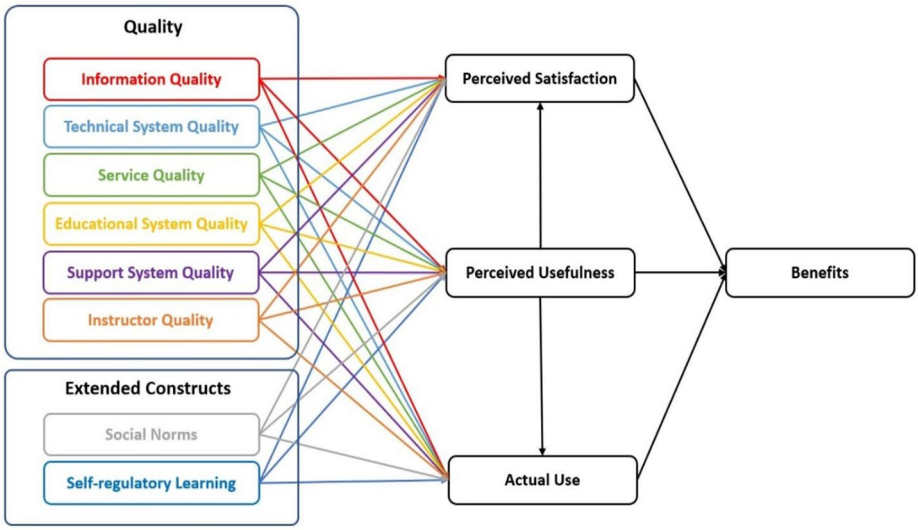

Fig. 2 Conceptual model. *Note*: Conceptual model used in the research study with the two additional constructs and the proposed relationships that lead to benefits

2.1 Hypothesis Development

The following sections explain the hypotheses developed from the conceptual model in Fig. 2.

2.1.1 Technical System Quality (TSQ)

Technical system quality measures the performance, reliability, and efficiency of an information system. DeLone and McLean (2003) highlighted that system quality, particularly technical quality, critically influences user satisfaction. Hassanzadeh et al. (2012) also found that users with less technical experience are more satisfied with a good system.

Perceived usefulness is a user's belief that a system will enhance job performance. Technical quality increases the perception of an information system's success and utility. Legramante et al. (2023) integrated the DeLone & McLean Information Systems Success Model with the Technology Acceptance Model to analyse user satisfaction in Moodle, showing that system quality is critical for perceived usefulness. Without technical quality, users may find a system useless. System usage depends entirely on technical quality. Azwar et al. (2022) highlighted that during the COVID-19 pandemic, system and service quality positively affected user satisfaction and continued system use. Therefore, drawing from prior studies, the current research proposes the following hypotheses:

H1a *Technical system quality positively influences perceived satisfaction.*

H1b *Technical system quality positively influences perceived usefulness.*

H1c *Technical system quality positively influences system use.*

2.1.2 Information Quality (IFQ)

Information quality includes relevance, accuracy, timeliness, and completeness of data. It is essential for users to fulfil their responsibilities and make the right choices. When information is relevant, accurate, timely, and customised, it leads to user satisfaction. DeLone and McLean (1992) emphasise that information quality is directly linked to user satisfaction, affecting the entire user experience and outcomes. Recent studies, such as Rustandi et al. (2023), confirm that information quality positively impacts user satisfaction.

Halawi et al. (2008) found that users' satisfaction increases with confidence in data accuracy. Perceived usefulness is tied to information quality. Li and Zhu (2022) found that in online learning platforms, information quality significantly affects user satisfaction, which in turn influences perceived usefulness. Chen and Tseng (2011) add that evaluating product reviews using an information quality framework shows how critical these dimensions are for user satisfaction and decision-making. Lwoga (2014) explains that system use is closely connected to information quality because users depend on it to achieve their goals. High information quality increases users' belief in the system's value for their jobs.

System use is directly connected to information quality. Rai et al. (2002) highlight that systems offering precise, relevant, and timely data are recommended for frequent use as they help users perform their jobs and make decisions. Halawi et al. (2008) argue that high information quality reduces uncertainty and increases user confidence, leading to greater system use. Conversely, low information quality results in lower utilisation. Susilowati (2020) demonstrated that information quality is the dominant variable affecting user satisfaction in academic information systems. Therefore, reflecting on the literature, this study formulates the following hypotheses:

H2a *Information quality positively influences perceived satisfaction.*

H2b *Information quality positively influences perceived usefulness.*

H2c *Information quality positively influences system use.*

2.1.3 Service Quality (SQ)

DeLone and McLean (1992) identified a clear impact of service quality on both system use and user satisfaction. Specifically, the service quality of IT services, whether in-house information systems or e-learning platforms, plays a crucial role in enhancing user satisfaction and positively influencing their use of the system. Akgul et al. (2024) integrated the DeLone and McLean model, among other theoretical frameworks, to examine the continued use of mobile learning (m-learning) in universities during the COVID-19 pandemic. The research highlighted that system quality significantly impacted students' intention to continue using m-learning platforms, emphasising the need for reliable and high-quality e-learning services, especially during crisis-induced transitions to remote learning. Moreover, studies by AL-Sabawy (2013) and Ngai et al. (2007) demonstrated that service quality significantly impacts perceived usefulness, a finding that aligns with the theoretical model developed by Lwoga (2014). Saputra and Sahona (2023) assessed student satisfaction with e-learning platforms using the DeLone and McLean model and found high levels of satisfaction among

students. Similarly, Al-azam et al. (2023) explored the impact of perceived utility, service quality, and information quality on students' behavioural intentions to engage in e-learning, emphasising the role of user satisfaction in this relationship. Therefore, based on the above discussion, this research posits the subsequent hypothesis:

H3a *Service quality positively influences perceived satisfaction.*

H3b *Service quality positively influences perceived usefulness.*

H3c *Service quality positively influences system use.*

2.1.4 Educational System Quality (ESQ)

Hassanzadeh et al. (2012) found that the quality of the educational system in Iranian universities directly and positively affects user satisfaction, which in turn indirectly influences system usage. Akgul et al. (2024) highlighted the role of attitude, perceived usefulness, satisfaction, and habit in continuing the use of mobile learning during the COVID-19 pandemic. Similarly, Al-azam et al. (2023) found that perceived utility, service quality, information quality, and ICT infrastructure significantly influence e-learning adoption in Yemeni public universities.

Bessadok and Bardesi (2023) examined how personal values impact e-learning adoption at King Abdulaziz University, revealing that students who prioritise self-enhancement and openness to change are more likely to engage in e-learning. Wijaya (2022) assessed the success of the Edmodo platform at Dinamika Bangsa University, noting that user satisfaction and system use strongly influenced its success. Safsouf et al. (2020) proposed the e-Learner Success Assessment Model (e-LSAM) to understand satisfaction, self-regulation, and continuance intention in Moroccan higher education, offering a comprehensive framework for evaluating e-learning success. Therefore, building on prior research, this paper articulates the following hypotheses:

H4a *Educational system quality positively influences perceived satisfaction.*

H4b *Educational system quality positively influences perceived usefulness.*

H4c *Educational system quality positively influences system use.*

2.1.5 Support System Quality (SSQ)

The impact of supportive factors on the success of e-learning systems can be seen in an empirical study conducted by Ozkan and Koseler (2009) at Brunel University. The study revealed a notable increase in the use of the Learning Management System (LMS) at the institution. This growth may be attributed to the institution's heightened focus on encouraging both students and professors to integrate LMS into their courses. Moreover, as Ozkan and Koseler (2009) note, the use of U-Link technology platforms has also surged in recent years due to the rising popularity of e-learning platforms. Furthermore, a study that examined the relationship between supportive systems and user satisfaction underscores the criti-

cal importance of institutional support in achieving successful e-learning outcomes. The research by Navimipour and Zareie (2015) indicates that promoting the use of e-learning systems in companies has a significant positive impact on employee satisfaction. This suggests that companies implementing e-learning tools, supported by institutional encouragement, are more likely to enhance user satisfaction. Given the existing body of knowledge, this study advances the following hypotheses:

H5a *Support system quality positively influences perceived satisfaction.*

H5b *Support system quality positively influences perceived usefulness.*

H5c *Support system quality positively influences system use.*

2.1.6 Instructor Quality (IQ)

Researchers in e-learning have explored the impact of instructors on e-learning success. Sun et al. (2008) investigated the correlation between instructor roles and e-learning outcomes, assessing factors like reaction timeliness and disposition toward e-learning. These factors significantly determine e-learning effectiveness. Similarly, Cidral et al. (2018) found a positive correlation between instructor quality and user satisfaction. Lwoga (2014) confirmed that higher-quality instructors contribute to the perceived usefulness and satisfaction of e-learning systems. Mtebe and Raphael (2018) also found that instructor calibre impacts learner satisfaction.

The concept of subjective norm, reflecting instructor influence on learner attitudes and behaviours, has been examined by Park (2011) and Roca et al. (2006). Both studies identified significant connections between perceived usefulness, enjoyment, and instructor roles. However, limited research directly examines the link between teacher quality and e-learning system utilisation. McGill and Klobas (2009) highlighted the importance of instructor norms in LMS adoption. Parameters related to teachers, such as positive attitude, enthusiasm, and recommendations, are highly valued by students. These qualities enhance student engagement, interactive communication, and timely responses, increasing e-learning effectiveness and positively influencing satisfaction and system use. Thus, instructor quality is crucial in shaping e-learning success. Thus, leveraging prior empirical evidence, we hypothesise:

H6a *Instructor quality positively influences perceived satisfaction.*

H6b *Instructor quality positively influences perceived usefulness.*

H6c *Instructor quality positively influences system use.*

2.1.7 Perceived Satisfaction (PS)

The validity and reliability of user satisfaction as a crucial metric for assessing the effectiveness of information systems, including e-learning systems, have been convincingly demonstrated. Within our research framework, we have assumed that user satisfaction is a key determinant of the benefits construct. This assumption is supported by empirical evidence

highlighting the significance of the DeLone and McLean model (DeLone & McLean, 2003). Hassanzadeh et al. (2012) explained that when users of an e-learning system experience higher satisfaction levels, they are more likely to derive significant benefits from using the system. This indicates that satisfaction not only reflects the immediate success of the system but also enhances the longer-term advantages associated with its use. Moreover, Cidral et al. (2018) found that 43.3% of the variance in satisfaction could be accounted for by perceived contentment, suggesting a strong correlation between the two. This finding is consistent with the results achieved by Eom and Ashill (2016), further reinforcing the importance of satisfaction in understanding the effectiveness and benefits of e-learning systems. Based on the findings of the above studies, we propose the following hypotheses:

H7 *Perceived satisfaction positively influences benefits.*

2.1.8 Perceived Usefulness (PU)

Davis (1989) used usefulness as a fundamental determining component in the technology adoption model. Acceptance is an essential factor in determining the effectiveness of information and e-learning systems (Davis, 1989; Roca et al., 2006). The study's model predicts that the perceived utility of e-learning will have a favourable impact on three factors: perceived satisfaction, use, and the advantages experienced by students. The literature results provide empirical evidence to support these relationships. Arbaugh (2000) confirmed that the perceived utility of course software positively correlates with student satisfaction in Internet-based courses. The research conducted by Seddon (1997) on information system success, AL-Sabawy (2013) on e-learning systems success, and Limayem and Cheung (2008) all concluded that perceived usefulness has a large and direct impact on user happiness. Similarly, if students regard the e-learning system as beneficial, they are more inclined to use it. This link has been evaluated in e-learning research, such as that conducted by Islam (2013), Pituch and Lee (2006), Van Raaij and Schepers (2008), and Sandjojo and Wahyuningrum (2015). Prior research has demonstrated a strong and direct correlation between usefulness and net benefits, usefulness and organisational benefit (Park et al., 2011), usefulness and individual impact (Lee et al., 2011), as well as usefulness and impact on both individuals and organisations.

Building on these foundational perspectives, recent studies in contemporary e-learning environments have further reinforced the critical role of perceived usefulness in shaping students' acceptance and continued use of digital learning systems. For instance, Barz et al. (2024) demonstrated that perceived usefulness significantly influences students' engagement and satisfaction, particularly when combined with self-regulatory learning capabilities in online environments. Similarly, Alkhawaja et al. (2022) found that perceived usefulness acts as a key mediating factor between system quality and students' intention to use e-learning systems. More recently, Tawafak et al. (2023) confirmed that perceived usefulness remains a significant predictor of behavioural intention and actual system use in higher education digital learning contexts. These findings highlight that, beyond its traditional role in technology adoption, perceived usefulness is closely associated with learning effectiveness, engagement, and sustained use in modern e-learning environments. Therefore, considering previous studies, this study establishes the following hypotheses:

H8a *Perceived usefulness positively influences perceived satisfaction.*

H8b *Perceived usefulness positively influences system use.*

H8c *Perceived usefulness positively influences benefits.*

2.1.9 Actual Use (AU)

The measure of actual system utilisation is a common factor in both the information systems success model (DeLone & McLean, 2003) and the Technology Acceptance Model (TAM) (Davis, 1989). Previous research has shown a high correlation between the use of the system and the advantages it offers (Chen & Tseng, 2011; Garcia-Smith & Effken, 2013). The use of e-learning systems at an organisational level has been shown to have a direct and favourable impact on the overall benefits of the firm (Chen & Tseng, 2011). Several other investigations have shown comparable findings (Halawi et al., 2008; Kositanurit et al., 2006; Zhu & Kraemer, 2005). Therefore, we anticipate that using the system would effectively improve students' advantages in terms of augmented knowledge, time efficiency, and systematic learning process management. Based on previous research, the present study offers the following hypotheses:

H9 *Actual use of SCM positively influences benefits.*

2.1.10 Self-regulatory Learning (SRL)

Self-regulatory learning (SRL) refers to the process where learners set their goals, monitor their progress, and adjust their behaviours accordingly to achieve academic success. SRL has been shown to be a significant predictor of student performance in online learning environments. Yavuzalp and Bahcivan (2021) demonstrated that students with strong self-regulatory learning skills are more likely to achieve better academic outcomes and express higher levels of satisfaction with e-learning systems. These findings are corroborated by Zimmerman and Schunk (2013), who found that SRL enhances learner autonomy and persistence, contributing to the success of e-learning. Accordingly, based on these studies, it is hypothesised that:

H10a *Self-regulatory learning positively influences students' perceived satisfaction with SCM systems.*

H10b *Self-regulatory learning positively influences students' perceived usefulness of SCM systems.*

H10c *Self-regulatory learning positively influences students' system use in SCM environments.*

2.1.11 Social Norm (SN)

Social norms, defined as the perceived expectations of significant others regarding an individual's behaviour, are crucial in shaping technology adoption in educational settings. Venkatesh and Davis (2000) emphasised that social norms can significantly influence the intention to adopt and use new technologies, as individuals are often driven by the expectations of their peers, instructors, or society. In the context of e-learning, research by Günther (2021) and Neubaum et al. (2023) has shown that social norms play a pivotal role in students' engagement and sustained use of online platforms, as learners tend to conform to the behaviours that are socially endorsed. Reflecting on these studies, we formulate the following hypothesis:

H11a *Social norms positively influence students' perceived satisfaction with SCM systems.*

H11b *Social norms positively influence students' perceived usefulness of SCM systems.*

H11c *Social norms positively influence students' system use in SCM environments.*

2.1.12 Benefit (BFT)

Perceived benefit in the context of e-learning refers to the extent to which users believe that using an e-learning system enhances their learning outcomes, skill acquisition, and overall educational experience. This concept is critical in understanding how users assess the value and effectiveness of e-learning systems. According to Holsapple and Lee-Post (2006), perceived benefit encompasses the tangible and intangible gains that learners experience as a result of using e-learning platforms, such as improved academic performance, flexibility in learning, and the ability to manage learning at one's own pace. This understanding of perceived benefits underpins our hypotheses that increased satisfaction with and usage of the e-learning system, along with perceived usefulness, are positively correlated with enhanced perceived benefits, driving both immediate and long-term educational success in the e-learning environment.

3 Research Methods

This section describes the research methods, including research design, survey instrument development, sample selection, data collection procedures, and the data analysis techniques employed. These methodological details provide the foundation for ensuring the validity, reliability, and robustness of the study's findings.

3.1 Research Design

This study employs a quantitative research design using a survey method to collect data from students using the SCM system. The survey includes constructs and items derived from the theoretical models discussed in this paper. This approach allows for the collection

of large amounts of data and the testing of relationships between variables (Creswell & Creswell, 2017).

3.2 Measurement Instruments

To ensure the validity of all measures, the measurement items for the latent constructs were adapted from previous studies. The detailed items of each construct and their sources are presented in Table 2.

3.3 Questionnaire Design and Data Collection

The questionnaire for this study was divided into Part A and Part B. Part A collected demographic information, while Part B included questions addressing different constructs presented in the research model, as depicted in Fig. 2. A 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5) was used for responses. The reason for adopting the five-point Likert scale over a seven or nine-point Likert scale is its simplicity (Zikmund et al., 2013). This scale was used to increase the response rate and response quality, along with reducing respondent burden (Zikmund et al., 2013). A pilot study was conducted to test the effectiveness and appropriateness of the questions and to ensure a clear understanding of the concept and items that help to prevent the respondents from developing their idiosyncratic meanings for the terms. The pilot study recruited 20 undergraduate and postgraduate students, including both new and continuing students with experience of traditional semester-based and Southern Cross Model delivery. Feedback from this pilot study was used to make context-specific adjustments to the questionnaire. The measurement model was further assessed for reliability using Cronbach's alpha and composite reliability, while validity was assessed using convergent and discriminant validity (Hair et al., 2022), which have been presented in Sect. 4.2.

Participants for the main study were recruited from the university's undergraduate and postgraduate students across all six campuses and online. A non-probability purposive or convenience sampling technique was used. This approach of data collection is easy to use, flexible, low-cost and time-saving Ruhl (2004), and is a commonly applied data collection technique in empirical studies (Hoque et al., 2017)**.** Data was collected through a cross-sectional survey from September 13 to October 27, 2023, using Qualtrics software. The survey was distributed electronically to students via group email and online learning platforms. Participants were provided with information explaining the research aim and objectives briefly and assured of confidentiality and anonymity to encourage honest reporting. Participation in the survey was considered consent. Students' participation was voluntary; answering questions was optional, and all responses were anonymous.

There is considerable variation in opinions regarding the optimum sample size for different types of statistical analysis (Hair Jr. et al., 1998). For example, structural equation modelling (SEM) recommends a sample size of 200 as fair and 300 as good (Kline, 2015). Hair et al. (1998) also recommended a sample size of 200 to test a model using SEM. Roscoe and Johni (1975) reported that in multivariate research, such as multiple regression analysis, the sample size should be at least 10 times the number of items in the study. Our proposed multivariate regression model consists of 51 items. As per Roscoe and Johni (1975) and previous studies, a sample size of 600 was targeted for data analysis using SEM.

3.4 Data Analysis

Data from the surveys were downloaded, cleaned and entered into spreadsheets. Initial data screening and cleaning were conducted to address missing values and outliers and ensure the accuracy of the data. A total of 101 of the 974 responses were excluded from the SEM analysis because they were incomplete; however, they were retained in the demographic summary presented in Table 3. The valid responses exceeded the necessary sample size, ensuring the robustness of the SEM analysis, which is a widely accepted paradigm for measuring the validity of a theory using empirical data (Götz et al., 2009). Descriptive statistics summarised the demographic characteristics of the sample and the distribution of responses for each survey item, shown in Table 3. The demographic characteristics of the respondents indicate a diverse representation of the SCU student body, providing a comprehensive dataset.

To select which statistical method to utilise, a researcher must first understand the assumptions underpinning both covariance-based structural equation modelling (CB-SEM) and partial least squares structural equation modelling (PLS-SEM). Hair et al. (2011) state that there are several general rules to follow when choosing between PLS-SEM and CB-SEM. For example, if the purpose of the research is to test or confirm a theory, then CB-SEM is a suitable method to utilise. This is because when testing a theory, it is required to determine the fit of observed data with the theoretical model (Barclay et al., 1995). On the other hand, PLS-SEM is suitable if the research goal is prediction and theory development. The aim of PLS SEM is to determine the most accurate forecast of variable relationships and to increase the level of shared variance between latent variables and a complex research model. Since the current study involves applying established theories to predict relationships in a new context, PLS-SEM was used in the first stage to test and validate the relationship between the proposed model and the hypothesised structure presented in Sects. 4.2–4.4. SEM is a widely accepted paradigm for measuring the validity of a theory using empirical data (Götz et al., 2009). Data analysis occurred using SmartPLS software for PLS-SEM (Hair et al., 2022). The data analysis was conducted in multiple stages to ensure alignment between the analytical procedures and the reported results. First, the measurement model was evaluated to assess the reliability and validity of the constructs using indicators such as Cronbach's alpha, composite reliability, and average variance extracted. Second, the structural model was assessed to test the hypothesised relationships using path coefficients, t-statistics, and significance levels. Finally, the predictive accuracy of the model was examined using R^2 and Q^2 values. The results of these analyses are presented in Sects. 4.2, 4.3, and 4.4, respectively.

Although PLS-SEM is a rigorous tool for theory development and predictive modelling, its conventional application primarily estimates linear relationships between constructs and may therefore fail to identify unmodelled nonlinear patterns (Richter & Tudoran, 2024). In the context of e-learning systems, recent empirical evidence suggests that student acceptance and satisfaction are often driven by complex, non-linear patterns that traditional structural equation modelling may fail to capture (Sarstedt & Liu, 2024). The adoption of specialised pedagogical frameworks such as the Block Model involves complex interactions between technical utility, pedagogical design, and user psychology that may not follow a strict linear pattern (Loh et al., 2024). Given the intensive, immersive, and psychologically demanding nature of Block Model e-learning systems, students' acceptance and satisfaction are likely shaped by non-linear relationships among technological and pedagogical factors

Table 2 Survey items

Constructs	Items	References
Benefit (BFT)	1: Using unit modules has increased my knowledge and helped me to be successful in my study 2: The SCM is a very effective educational system and has helped me to improve my learning process 3: The SCM has helped me to achieve the learning goals of my study program 4: Studying under the SCM has helped me to develop my critical thinking skills	(DeLone & McLean, 2003; Hassanzadeh et al., 2012; Holsapple & Lee-Post, 2006)
Information quality (IFQ)	1: Information and resources needed from the learning sites are always accessible 2: The structure of MySCU learning sites is well organised into logical and understandable components 3: Information from MySCU learning sites is in a form that is readily usable 4: I perceive the design of MySCU learning sites (e.g., fonts, style, colour, images, videos) to be good and meets the quality standards	Ozkan & Koseler, 2009; Selim, 2003
Technical system quality (TSQ)	1: It is easy to use the MySCU learning sites 2: It is easy to understand the structure of MySCU learning sites and how to use it 3: MySCU learning sites meet my requirements, and I can find the information I need 4: MySCU learning sites include the necessary features and functions I need 5: MySCU learning sites are always available for me to perform learning activities 6: MySCU learning sites launch and run right away 7: MySCU learning sites do not crash frequently	(Sedera et al., 2004; DeLone & McLean, 2003)
Service quality (SQ)	1: There are enough and clear instructions/training about how to use MySCU learning sites 2: MySCU learning sites provide proper online assistance and help 3: The IT services staff is available and cooperative when facing an error at MySCU learning sites 4: The IT services staff understands the specific needs of students using learning sites 5: I receive a satisfactory and timely response from the IT services staff regarding using learning sites	(Holsapple & Lee-Post, 2006; Ozkan & Koseler, 2009)
Support service quality (SSQ)	1: MySCU learning sites provide appropriate information about academic misconduct issues when submitting assignments through the system 2: I feel student support facilities, such as library resources and services, are adequate 3: MySCU learning sites provide information about where I can get further academic help if needed	(Khan, 2005; Ozkan & Koseler, 2009)

Table 2 (continued)

Constructs	Items	References
Educational system quality (ESQ)	1: I feel the assessments for units in the new Southern Cross model (SCM) are appropriate for the learning content 2: I believe the online content in each module provides various appropriate and varied learning media (e.g., video, audio, images, text, quizzes, etc.) for my study 3: I have the opportunity to discuss concepts with peers and teachers through the discussion forum, chats, online, or face-to-face tutorials 4: I believe the contents provide engaging learning through checking my understanding and providing automated feedback on my learning progress 5: I believe the teaching in the workshops and tutorials is relevant and engaging 6: I believe I can learn effectively within the time constraints of the SCM 7: I believe the content modules, including online materials, tutorials and workshops, are well organised and sequenced to help me build my knowledge and skills towards the assessment items	(Hassanzadeh et al., 2012; Selim, 2003; Sun et al., 2008)
Instructor quality (IQ)	1: Generally, my instructors have a positive attitude toward the SCM 2: I think an instructor's enthusiasm for the SCM stimulates my desire to learn 3: I receive prompt responses to questions and concerns from my instructors in the SCM	(Ozkan & Koseler, 2009; Sun et al., 2008)
Social norm (SN)	1: People who influence my behaviour think I should study under the SCM 2: People who are important to me think I should study under the SCM 3: There are lecturers who make using Unit modules genuinely useful	(Venkatesh et al., 2003; Yoo et al., 2012)
Self-regulatory learning (SRL)	1: When it comes to learning and studying, I am a self-directed person 2: In my studies, I am self-disciplined and find it easy to set aside reading and homework time 3: I work strategically to priorities tasks to help me achieve my learning goals in the SC model 4: I am able to manage my study time effectively and easily complete assignments on time	(Al-Adwan et al., 2018)
Perceived satisfaction (PS)	1: I enjoy studying within the SCM 2: Unit modules in the SCM satisfy my educational needs 3: I enjoy the shorter time of learning in the SCM 4: Overall, I am pleased with the experience of SCM learning	(Hassanzadeh et al., 2012);

Table 2 (continued)

Constructs	Items	References
Perceived usefulness (PU)	1: Using unit modules enables me to accomplish my learning tasks more quickly	(Pituch & Lee, 2006; Rai et al., 2002; Selim, 2003; Venkatesh & Davis, 2000)
	2: Using unit modules improves my learning performance	
	3: Using unit modules helps me learn effectively	
	4: Overall, unit modules are useful	
Actual use (AU)	1: I use MySCU unit sites frequently to access the content	(DeLone & McLean, 2003; Rai et al., 2002; Selim, 2003)
	2: I depend on MySCU unit sites in my study	
	3: I use MySCU unit sites regularly	

Table 3 Demographics of respondents

Sample characteristic	Frequency	Percentage
Gender		
Male	233	23.92
Female	722	74.13
Other	8	0.82
Not to Say	11	1.13
Total	974	100.00
Age		
<20 years	61	6.26
20–29	335	34.39
30–39	264	27.10
40–49	181	18.58
50–59	98	10.06
60-above years	35	3.59
Total	974	100.00
Enrolled course		
Undergraduate	798	81.93
Postgraduate	176	18.07
Total	974	100.00
Language		
English	694	71.25
Other	280	28.75
Total	974	100.00
Did you study part of your degree traditionally (T&L Model)?		
Yes	665	68.28
No	309	31.72
Total	974	100.00
Are you an on-campus student?		
Yes	426	43.74
No	548	56.26
Total	974	100.00

and their cognitive responses (Sangwan et al., 2024). To address these methodological gaps, this study integrates an Artificial Neural Network (ANN) approach into data analysis. As a second-stage analytical technique, ANN complements the PLS-SEM analysis by capturing complex and potentially non-linear relationships among the study variables (Hair et al., 2022), as presented in Sect. 5. Moreover, NN modelling ranks the key antecedents and validates the PLS-SEM result. The NN model ensures reliability in the validation of the construct, even for the users' non-compensatory decisions. While PLS-SEM provides a linear, theory-driven assessment of the hypothesised relationships, the ANN model enhances predictive capability and allows for a more robust evaluation of the key determinants. The ANN results, including model validation and sensitivity analysis, are presented in Sect. 5. This study, therefore, presents a more robust and predictive model that can overcome the fundamental constraints of the existing model and provide a predictive analysis of the benefits of using the SC model by students.

4 Results

4.1 Demographic Profile of Respondents

The demographic profile of the 974 respondents indicates a predominantly female sample (74.13%), with males representing 23.92% and only a small proportion identifying as other or preferring not to disclose. The majority of participants were relatively young, with most aged between 20–29 years (34.39%) and 27.10% of respondents aged 30–39 years. A large proportion of respondents were enrolled in undergraduate programs (81.93%), and English was reported as the primary language by 71.25% of the sample. Furthermore, most students had prior experience with traditional semester or trimester-based teaching and learning models (68.28%), while over half were studying off-campus (56.26%), reflecting a diverse cohort engaging with the newly introduced SC model delivery. The demographic composition of the sample is shown in Table 3.

Overall, the demographic profile reflects a diverse student cohort, with a strong representation of undergraduate and online learners. The relatively high proportion of off-campus students highlights the relevance of the SC Model within a digitally mediated learning environment, where flexibility and accessibility are critical. In addition, the presence of students with prior experience in traditional teaching and learning models provides a useful basis for comparing perceptions of the block model approach. The wide age distribution, including a significant number of mature-age students, further suggests that the findings capture varied learning needs and experiences. These characteristics support the suitability of the sample for examining student acceptance, satisfaction, and usage behaviour in contemporary e-learning contexts.

The following section presents the results of the data analysis, beginning with the evaluation of the measurement model to confirm the reliability and validity of the constructs, followed by the assessment of the structural model, hypothesis testing, and predictive accuracy of the proposed framework.

4.2 Measurement Model Testing

Following the analytical procedure outlined in Sect. 3.4, the measurement model was first evaluated to assess reliability and validity. The measurement model was assessed for reliability using Cronbach's alpha and composite reliability, while validity was assessed using convergent and discriminant validity (Hair et al., 2022).

4.2.1 Convergent Validity

As per Table 4, internal reliability was confirmed through Cronbach's alpha values ranging from 0.801 to 0.961 and composite reliability (CR) values ranging from 0.803 to 0.963, indicating strong internal consistency (Hair et al., 2022). Convergent validity was demonstrated with item loadings between 0.690 and 0.967 and average variance extracted (AVE) values between 0.608 and 0.895, both of which exceeded standard thresholds. Consequently, the conditions for convergent validity are met (Hair et al., 2022).

Table 4 The measurement model

Constructs	Items	Loadings	AVE	CR	Cronbach's alpha
Benefit (BFT)	BFT1	0.789	0.830	0.940	0.930
	BFT2	0.954			
	BFT3	0.957			
	BFT4	0.934			
Information quality (IFQ)	IFQ1	0.849	0.751	0.891	0.889
	IFQ2	0.888			
	IFQ3	0.893			
	IFQ4	0.835			
Technical system quality (TSQ)	TSQ1	0.849	0.687	0.930	0.924
	TSQ2	0.851			
	TSQ3	0.869			
	TSQ4	0.877			
	TSQ5	0.833			
	TSQ6	0.787			
	TSQ7	0.728			
Service quality (SQ)	SQ1	0.793	0.608	0.876	0.845
	SQ2	0.846			
	SQ3	0.814			
	SQ4	0.718			
	SQ5	0.718			
Support service quality (SSQ)	SSQ1	0.829	0.608	0.876	0.845
	SSQ2	0.848			
	SSQ3	0.884			
Educational system quality (ESQ)	ESQ1	0.840	0.676	0.924	0.920
	ESQ2	0.818			
	ESQ3	0.773			
	ESQ4	0.860			
	ESQ5	0.804			
	ESQ6	0.787			
	ESQ7	0.869			
Instructor quality (IQ)	IQ1	0.886	0.733	0.820	0.818
	IQ2	0.859			
	IQ3	0.823			
Social norm (SN)	SN1	0.908	0.724	0.803	0.801
	SN2	0.917			
	SN3	0.712			
Self-regulatory learning (SRL)	SRL1	0.690	0.619	0.860	0.806
	SRL2	0.778			
	SRL3	0.841			
	SRL4	0.875			
Perceived satisfaction (PS)	PS1	0.967	0.895	0.963	0.961
	PS2	0.931			
	PS3	0.920			
	PS4	0.965			
Perceived usefulness (PU)	PU1	0.895	0.853	0.943	0.942
	PU2	0.935			
	PU3	0.941			
	PU4	0.922			

Table 4 (continued)

Constructs	Items	Loadings	AVE	CR	Cronbach's alpha
Actual use (AU)	AU1	0.912	0.846	0.916	0.909
	AU2	0.924			
	AU3	0.922			

Table 5 The correlation matrix and the square root of the AVE

	AU	BFT	ESQ	IFQ	IQ	PS	PU	SN	SQ	SRL	SSQ	TSQ
AU	**0.920**											
BFT	0.288	**0.911**										
ESQ	0.287	0.826	**0.822**									
IFQ	0.484	0.518	0.619	**0.784**								
IQ	0.245	0.769	0.798	0.522	**0.856**							
PS	0.185	0.776	0.677	0.496	0.653	**0.946**						
PU	0.360	0.600	0.577	0.604	0.502	0.636	**0.924**					
SN	0.295	0.742	0.700	0.478	0.695	0.632	0.503	**0.851**				
SQ	0.405	0.433	0.512	0.680	0.423	0.403	0.484	0.410	**0.780**			
SRL	0.239	0.507	0.517	0.365	0.505	0.461	0.346	0.485	0.336	**0.787**		
SSQ	0.331	0.541	0.627	0.551	0.546	0.417	0.382	0.499	0.543	0.451	**0.854**	
TSQ	0.296	0.561	0.685	0.664	0.569	0.459	0.395	0.519	0.565	0.422	0.708	**0.829**

4.2.2 Discriminant Validity

The discriminant validity was calculated using the AVE's square root and cross-loading matrix. As per Hair et al. (2011), the square root of the AVE of a construct should be greater than its correlation with other constructs for satisfactory discriminant validity. The diagonal values should be larger than all other construct entries in the corresponding columns and rows to satisfy discriminant validity and be confident that the value is not associated with confounding factors and is distinct from other variables (Rönkkö & Cho, 2022). Table 5 demonstrates the correlation matrix for the Fornell-Larcker approach (Fornell & Larcker, 1981). It is apparent that the diagonal values are greater than the other numbers inside the same column and rows, except between ESQ and BFT. However, this violation was very marginal and determined to be negligible. Overall, testing confirms the discriminant validity of the data.

Another more recent and stringent measure called the Heterotrait-Monotrait ratio of correlations (HTMT) is also used to assess discriminant validity in PLS. To confirm the discriminant validity, the obtained values should be lower than the threshold value of HTMT 0.90 (Gold et al., 2001; Henseler et al., 2015). As shown in Table 6, all HTMT index values are less than 0.900, confirming liberal discriminant validity.

4.3 Hypothesis Testing

In line with the second stage of the analysis described in Sect. 3.4, the structural model was evaluated to test the hypothesised relationships between the constructs. Path coefficients, R-squared values, and the significance of the paths were examined to determine the strength and direction of the relationships (Hair et al., 2022). The significance of the path coeffi-

Table 6 Heterotrait-Monotrait ratio (HTMT)

	AU	BFT	ESQ	IFQ	IQ	PS	PU	SN	SQ	SRL	SSQ	TSQ
AU												
BFT	0.316											
ESQ	0.314	0.887										
IFQ	0.561	0.454	0.526									
IQ	0.283	0.883	0.717	0.47								
PS	0.195	0.817	0.707	0.46	0.734							
PU	0.385	0.647	0.616	0.651	0.572	0.668						
SN	0.344	0.861	0.808	0.452	0.858	0.719	0.579					
SQ	0.43	0.496	0.589	0.697	0.517	0.436	0.506	0.505				
SRL	0.289	0.605	0.609	0.347	0.644	0.536	0.406	0.619	0.427			
SSQ	0.381	0.628	0.73	0.516	0.672	0.471	0.435	0.619	0.676	0.574		
TSQ	0.319	0.608	0.742	0.567	0.65	0.483	0.419	0.599	0.655	0.497	0.817	

cient was evaluated using the bootstrapping algorithm in PLS, generating 5000 bootstrap samples. The *t* and *p* values determined the statistical significance of the path coefficients (β values) at a level of significance (α) of 0.05, and the t value is greater than 1.96. The results of the hypothesis test are demonstrated in Table 7.

The hypothesis testing results reveal that Technical System Quality (TSQ), Information Quality (IFQ), Service Quality (SQ), Educational System Quality (ESQ), and Social Norm (SN) are positively associated with the Perceived Usefulness (PU) of SCM. Educational System Quality (ESQ), Instructor Quality (IQ), Perceived Usefulness (PU), Self-Regulatory Learning (SRL), and Social Norm (SN) influence students' satisfaction with SCM. Technical System Quality (TSQ), Information Quality (IFQ), Service Quality (SQ), Educational System Quality (ESQ), Support Service Quality (SSQ), Perceived Usefulness (PU), and Social Norm (SN) influence students' interaction with the SC Model learning environment.

Moreover, Perceived Satisfaction (PS), Perceived Usefulness (PU), and Actual Use (AU) affect the perceived benefit of learning through SCM. Therefore, the majority of hypotheses were accepted. On the other hand, Support Service Quality (SSQ), Instructor Quality (IQ), and Self-Regulatory Learning (SRL); Technical System Quality (TSQ), Information Quality (IFQ), Service Quality (SQ), Support Service Quality (SSQ); and Instructor Quality (IQ) and Self-Regulatory Learning (SRL) did not show significant association with Perceived Usefulness (PU), Perceived Satisfaction (PS), and Actual Use (AU) behaviour of SCM. Therefore, they were rejected.

4.4 Predictive Accuracy

The predictive accuracy of the model was then assessed, as outlined in Sect. 3.4, using R^2 and Q^2 values. Coefficient of determination (R^2) and predictive ability (Q^2) analyses were used to evaluate the predictive accuracy of the proposed model. A bootstrapping procedure with 5000 resamples was conducted to test all paths (Chin et al., 2020). Additionally, the blindfolding method was used to calculate Q^2 estimates. Table 8 shows that all dependent variables have Q^2 estimates above 0, and R^2 values exceeding 0.25, confirming that the proposed model demonstrates sufficient predictive accuracy (Hair et al., 2019, 2022; Henseler et al., 2009).

Table 7 Hypothesis testing

Hypothesis	Path	Beta (β)	*t* statistics	*p* values	Comment
H1a	TSQ -> PS	0.004	0.084	0.933	Rejected
H1b	TSQ -> PU	0.233	4.949	0.000	Accepted
H1c	TSQ -> AU	0.120	2.112	0.035	Accepted
H2a	IFQ -> PS	− 0.015	0.379	0.704	Rejected
H2b	IFQ -> PU	0.418	8.582	0.000	Accepted
H2c	IFQ -> AU	0.393	7.224	0.000	Accepted
H3a	SQ -> PS	− 0.006	0.198	0.843	Rejected
H3b	SQ -> PU	0.114	2.616	0.009	Accepted
H3c	SQ -> AU	0.116	2.557	0.011	Accepted
H4a	ESQ -> PS	0.211	4.299	0.000	Accepted
H4b	ESQ -> PU	0.293	5.309	0.000	Accepted
H4c	ESQ -> AU	0.128	2.070	0.039	Accepted
H5a	SSQ -> PS	− 0.069	1.798	0.072	Rejected
H5b	SSQ -> PU	− 0.036	0.836	0.403	Rejected
H5c	SSQ -> AU	0.134	2.534	0.011	Accepted
H6a	IQ -> PS	0.192	4.391	0.000	Accepted
H6b	IQ -> PU	0.034	0.697	0.486	Rejected
H6c	IQ -> AU	− 0.071	1.268	0.205	Rejected
H7	PS -> BFT	0.672	28.028	0.000	Accepted
H8a	PU -> PS	0.332	10.019	0.000	Accepted
H8b	PU -> AU	0.091	2.052	0.040	Accepted
H8c	PU -> BFT	0.130	5.166	0.000	Accepted
H9	AU -> BFT	0.117	5.011	0.000	Accepted
H10a	SRL -> PS	0.088	3.364	0.001	Accepted
H10b	SRL -> PU	0.026	0.784	0.433	Rejected
H10c	SRL -> AU	0.060	1.438	0.150	Rejected
H11a	SN -> PS	0.183	5.330	0.000	Accepted
H11b	SN -> PU	0.154	3.894	0.000	Accepted
H11c	SN -> AU	0.119	2.783	0.005	Accepted

Table 8 Predictive accuracy

Constructs	R^2	Q^2
AU	0.283	0.253
BFT	0.632	0.648
PS	0.596	0.531
PU	0.494	0.461

Table 8 shows that the model explains 28.3% of the variance in Actual Use (AU), and Benefits (BFT) shows strong explanatory and predictive power with 63.2% of the variance explained. Perceived Satisfaction (PS) has significant explanatory power and robust predictive relevance of 59.6%. Perceived Usefulness (PU) reflects moderate explanatory power and good predictive relevance with 49.4% of the variance. Overall, the model demonstrates substantial predictive accuracy, confirming its effectiveness with all R^2 values above 0.25 and Q^2 values above 0 (Sharma et al., 2021).

5 Artificial Neural Networking Analysis

The architecture of artificial neural networks is similar to that of the human brain, which is made up of synapses, axons, and neurons. Through the learning process, it can enhance knowledge (Ooi et al., 2018). The main advantage of neural networks (NN) lies in their ability to measure complex linear and non-linear interactions between predictors, make decisions on which predictors to accept and determine the priority and significance of each factor (Chan & Chong, 2012).

5.1 Validation of Neural Network

This study utilised the SPSS 23.0 software package to conduct neural network analysis. The neural network model was constructed using the multilayer perceptron training method and included a single hidden layer, as one hidden layer is sufficient to represent a continuous function adequately. To address the issue of overfitting, we employed a ten-fold cross-validation technique. In this study, 70% of the data was designated for training the neural network model, while the remaining 30% was used to test the prediction accuracy of the trained model (Chong, 2013). The input layer employed eleven constructs: information quality, technical system quality, service quality, educational system quality, support system quality, instructor quality, social norm, self-regulatory learning, perceived satisfaction, perceived usefulness and actual use, whereas the output layer is Benefit. The average cross-validated Root Mean Square Error (RMSE) values for training and testing were 5.155 and 0.341, respectively (Table 9). These low RMSE values indicate that the neural network model is reasonably consistent in explaining the numerical correlations between predictors and output.

5.2 Ranking of Factors

A sensitivity analysis of the neural network model was performed to rank the predictors according to their relative value. The relative importance of the predictors is a measure of the degree to which the network's model predicted changes in the data (Chong, 2013). Output values are related to variations in the values of the independent variables.

Table 9 RMSE for the artificial neural network

Network	RMSE (training)	RMSE (testing)
ANN1	6.101	0.239
ANN2	4.566	0.374
ANN3	5.385	0.467
ANN4	4.704	0.265
ANN5	4.575	0.332
ANN6	5.238	0.32
ANN7	6.514	0.293
ANN8	4.535	0.391
ANN9	4.977	0.363
ANN10	4.951	0.363
Mean	5.155	0.341
Standard deviation	0.644	0.0628

Table 10 Comparison of PLS-SEM and neural network

Neural Network				PLS-SEM		
Factors	Relative Importance	Normalised importance (%)	Ranking	Factors	Path Coefficient	Ranking
PS	0.137	100	1	ESQ	0.416	1
PU	0.132	71	2	PS	0.314	2
IQ	0.12	65	3	SN	0.156	3
ESQ	0.096	56	4	IQ	0.133	4
SN	0.092	53	5	PU	0.058	5
IFQ	0.092	49	6	AU	0.054	6
SRL	0.089	49	7	SSQ	0.027	7
SQ	0.088	46	8	TSQ	0.001	8
SSQ	0.081	45	9	IFQ	− 0.1	9
AU	0.073	44	10	SRL	− 0.004	10
TSQ	0.071	43	11	SQ	− 0.026	11

A comparison between the results obtained from PLS-SEM analysis and neural network analysis, as outlined in Table 10, highlights the similarities and differences in determining the importance of predictors for E-learning 'Benefit'. In the SEM approach, the importance of predictors was evaluated based on the total un-standardised effects of each independent construct on the dependent construct. The SEM results identified educational system quality as the most significant determinant. Conversely, neural network analysis, which assessed independent variable importance scores, found satisfaction to be the most influential factor. The discrepancies between the two methods underscore the advantages of using a machine learning tool like neural networks, which can capture non-linear relationships and offer greater predictive accuracy compared to traditional statistical methods like PLS-SEM, which are limited to analysing linear relationships. This two-step process is crucial for progressing research on Block Model e-learning systems, given that it overcomes the analytical constraints of existing studies and provides a more detailed insight into student behavior within these unique learning environments.

6 Discussion

The following discussion interprets the key findings from both the PLS-SEM and ANN analyses, highlighting the most influential factors affecting student satisfaction, perceived usefulness, system use, and overall learning benefits. This study offers insights into factors affecting user satisfaction, perceived usefulness, actual usage, and student benefits within block model e-learning systems such as the SCM-learning system. The quality of technology service (TSQ) positively impacts actual usage and perceived usefulness but does not affect satisfaction. These findings align with DeLone and McLean (2003), as system quality affects usage through operational ease and perceived benefits. However, TSQ does not impact satisfaction. Some studies, like Roca et al. (2006), emphasise that content quality, instructor presence, and interactive features influence satisfaction in e-learning. Even if a platform is technically sound, students may not feel satisfied if content engagement or instructor interaction is lacking. Students are more likely to use the system regularly if it is stable and easy to navigate. However, this study did not find a significant relationship between Perceived Satisfaction (PS) and Perceived Usefulness (PU). This may be because

satisfaction depends on quality learning materials, instructional effectiveness, and interactive features (Roca et al., 2006). Self-regulatory learning (SRL) boosts satisfaction, showing that students report greater satisfaction when they feel empowered and confident in their learning (Liaw & Huang, 2013). However, Broadbent and Poon (2015) demonstrated that SRL does not directly influence perceived usefulness or actual use. Service quality (SQ) positively affects actual use and perceived usefulness, highlighting the importance of high-quality services in making the system appealing and practical for students (Kallweit et al., 2014). However, our findings suggest that SQ does not significantly impact satisfaction, indicating that services alone do not determine user satisfaction. This contradicts the existing research of Motaghian et al. (2013) and Zaidi et al. (2014), which only looked at the technical side.

Instructor Quality (IQ) significantly enhances perceived satisfaction (PS), confirming Dachner and Saxton (2015) and Canales and Maldonado's (2018) research that high-quality instructors are crucial for user satisfaction. However, the study found no significant impact of factors like the instructor's communication, responsiveness, and attitude toward the e-learning system on Perceived Usefulness (PU) and Actual Usage (AU). This contrasts with earlier studies that identified a positive relationship between instructor quality and the usage or intention to use e-learning systems (Abbas, 2016). Perceived usefulness and actual usage are influenced by the design and content quality of the e-learning platform rather than instructor quality alone (Martin et al., 2018). Educational System Quality (ESQ) has a strong association with satisfaction, perceived usefulness, and actual use. This result is consistent with findings by Hassanzadeh et al. (2012), underscoring the critical role of ESQ in fostering effective educational environments. The primary focus of the SCM and its success was on improving the quality of the teaching and learning system. Social Norms (SN) positively influence all dependent variables, highlighting the significant role of peer influence and societal expectations in shaping user behaviour and perceptions (Abdullah et al., 2016). Social norms are particularly influential in collective learning environments, where peer and instructor expectations shape individual engagement and persistence with e-learning systems (Venkatesh et al., 2003). Additionally, Günther (2021) found that fostering positive social norms significantly increases student participation and collaboration within online learning platforms, leading to better educational outcomes.

Information quality (IFQ) enhances Actual Use (AU) and Perceived Usefulness (PU), indicating the importance of IFQ in user engagement and perceived utility but not satisfaction. Information quality aspects such as providing students with sufficient and required information, concise and clear information, updated content, and attractively designed content contribute to their overall actual use. These results are corroborated by Hassanzadeh et al. (2012) research. However, information quality does not significantly influence student satisfaction, which is inconsistent with DeLone and McLean (2003) research. Perceived satisfaction in e-learning is influenced by various factors, including content relevance, instructor quality, interactivity, and engagement (Martin et al., 2018). The findings show a significant relationship between perceived satisfaction (PS) and the benefits (BFT) of learning using the SCM. This significant relationship is consistent with findings from other e-learning studies (Aparicio et al., 2017; Cidral et al., 2018; Seta et al., 2018). The SCM's success and effectiveness in increasing student satisfaction were predictable, given that enhancing student satisfaction was one of the primary focuses of the study.

The study's findings show that perceived usefulness (PU) is crucial in determining students' perceived satisfaction, benefit, and actual usage of the SCM. Students feel more satisfied when they believe the system enhances their learning performance, helps them complete tasks efficiently, and improves their learning effectiveness. When students perceive the e-learning system as beneficial, they are more inclined to use it. These results align with various e-learning studies (Al-Sabawy, 2013; Ghazal et al., 2018; Islam, 2013). The findings also show a positive association between the SCM's actual usage and the benefits derived from using it. Aligning e-learning systems with students' needs enhances academic performance, facilitates smoother interactions, and aids in achieving learning objectives. E-learning platforms offer efficiencies by simplifying resource searches, saving time, and minimising costs compared to traditional methods. Increased usage of e-learning systems correlates with greater benefits for students, consistent with prior research (Aparicio et al., 2017; Cidral et al., 2018). A comparison between PLS-SEM and neural network analysis highlights similarities and differences in determining predictors for the EBM system's benefit. Both methods show that perceived satisfaction is a central predictor of e-learning system success, reinforcing its significant role in any operationalisation modelling process.

7 Implications and Contribution

This study offers several important theoretical and practical implications for understanding student acceptance and use of e-learning systems within the SC Model and models like it. The key implications are discussed in detail in this section.

7.1 Theoretical

This study offers several theoretical implications. Firstly, it validates the well-established E-learning System Success (EESS) model (Al-Fraihat et al., 2020) in an innovative block-based learning structure, expanding its application beyond traditional e-learning environments. The model's constructs, such as system quality, information quality, and service quality, remain robust in influencing perceived usefulness, satisfaction, and usage. Secondly, the study extends the EESS model (Al-Fraihat et al., 2020) by incorporating Social Norms (SN) and Self-Regulatory Learning (SRL), addressing the complexity of modern e-learning environments. This contributes to a broader understanding of how peer influence and self-regulation affect student engagement, satisfaction, and perceived usefulness in block-based education. The findings align with prior research, indicating that social expectations and self-regulation influence the sustained use of e-learning. Thirdly, the comparison between Partial Least Squares Structural Equation Modelling (PLS-SEM) and ANN analysis shows the value of using machine learning for capturing non-linear relationships in educational research. This insight encourages future studies to combine traditional and machine learning approaches for a more comprehensive understanding of predictors in e-learning. The findings could be easily adapted or modified to assist in research on the adoption of the block e-learning model in other universities.

7.2 Practical

This study has important practical implications. Promoting self-regulatory learning through goal-setting, progress tracking, and personalised learning analytics can foster independent learning and long-term student engagement. Maintaining high service quality and instructor quality, along with incorporating social interaction opportunities, can enhance student retention and satisfaction. To sustain user engagement, a feedback-driven, student-centred approach with regular platform updates and interactive elements is recommended. Using data analytics to monitor system performance and guide improvements can help ensure the platform remains relevant and effective, supporting long-term student success. Social norms and educational quality play a significant role in student retention. By incorporating opportunities for social interaction and community building within the e-learning platform, institutions can reduce dropout rates and enhance social skills development. Ensuring that the platform's features are linked to better academic and professional prospects will enhance its perceived value, leading to greater student retention and academic success. By applying these practical strategies, SCU can create a sustainable and resilient e-learning environment that adapts to the evolving needs of students, ensuring their satisfaction and success throughout their academic journey.

8 Recommendations, Limitations and Future Research

The findings support the following recommendations for improving learning systems. Universities should focus on both technological and pedagogical factors. The study emphasises the need to enhance technical system quality, particularly reliability and usability, to increase perceived usefulness, actual system use, and student engagement. Strengthening support and service features, such as responsive IT and academic assistance, is identified as essential for improving student satisfaction. The study also underscores the importance of promoting self-regulatory learning strategies, including time management and goal setting, to accommodate diverse learning styles. Additionally, leveraging instructional and social factors, such as teacher behaviours, educational system design, and social norms, is shown to positively influence perceived usefulness, enjoyment, and collaborative engagement in e-learning environments.

The paper acknowledges several limitations that may have influenced its findings, particularly the uneven experience levels of participants with the block model, which could have introduced perception bias regarding the learning management system and institutional support. To address these gaps, the authors propose multiple directions for future research, including examining experience-related bias, exploring paradoxes in technical system quality, and identifying which support services most strongly drive satisfaction and continued use. Further research is also encouraged on self-regulatory learning across demographic groups, instructional and social influences on engagement, and longitudinal changes in satisfaction and perceived usefulness. Finally, the study calls for replication across different educational and cultural contexts to test the generalisability of its findings. These suggestions may improve e-learning platforms, increase their efficacy and usability and enhance student learning and outcomes.

9 Conclusions

This study analyses factors contributing to the success of immersive e-learning environments within the block model of higher education. Integrating established frameworks in information systems success and technology acceptance extends our understanding of critical drivers of student engagement, satisfaction, and learning outcomes in digital education. The findings highlight that system quality, information quality, and service quality are pivotal in shaping students' perceptions of usefulness and satisfaction with the e-learning platform. These elements significantly influence continued system use and perceived benefits, key indicators of overall e-learning success. The study also identifies social norms and self-regulatory learning as essential components in enhancing student engagement and satisfaction. While technical and informational aspects are critical, social and behavioural dimensions play a significant role in fostering deeper learner engagement and sustained platform use. These insights suggest that higher education institutions should focus on both digital infrastructure quality and cultivating an environment that supports self-regulatory learning and leverages social norms. The practical implications are clear: universities must adopt a holistic approach, considering both technical design and the social context of learning. By improving system quality, ensuring high-quality information and services, and fostering supportive social environments, institutions can significantly enhance student satisfaction and learning outcomes. Future research should explore how these factors interact in different e-learning models and contexts, refining the framework for e-learning success. This study contributes valuable knowledge for educators and administrators seeking to advance digital learning strategies in higher education.

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Data availability Data will be available on request.

Declarations

Conflict of interest No potential conflicts of interest were reported by the author(s).

Ethical approval

Ethical approval for the study was granted by the Human Research Ethics Committee of Southern Cross University, Australia, adhering to the National Statement on Ethical Conduct in Human Research 2023 (The Approval number is ECN-2023/142).

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Authors and Affiliations

Golam Sorwar[1] · Reza Ghanbarzadeh[1] · Jenelle Benson[1] · Raina Mason[1] · Md. Yahin Hossain[2]

✉ Golam Sorwar
golam.sorwar@scu.edu.au

Reza Ghanbarzadeh
Reza.ghanbarzadeh@scu.edu.au

Jenelle Benson
jenelle.benson@SCU.edu.au

Raina Mason
raina.mason@scu.edu.au

Md. Yahin Hossain
md.yahin_bba@rpsu.edu.bd

[1] Southern Cross University, Gold Coast Campus, Southern Cross Drive, Bilinga, QLD 4225, Australia

[2] Department of Business Administration, R. P. Shaha University, Narayanganj, Bangladesh