Social network for collaborative learning: what are the determining factors?

Paschal Kpimekuu Boruzie1 · Emmanuel Awuni Kolog1 · Eric Afful-Dazie1 · Sulemana Bankuoru Egala2

Accepted: 26 October 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
Despite the disruptiveness caused by the COVID-19 pandemic in the Global South, the superficial and lacklustre use of information technology has been exposed, especially in the education sector. Meanwhile, the early stages of the pandemic saw academic institutions racing up to harness digital learning solutions, including social networks, to facilitate teaching and learning. By sampling 360 students from higher education institutions (HEIs) in Ghana, a partial least square structural equation modelling, in this study, was leveraged to explore the determinants of using social networks for collaborative learning. After analysing the data, this study shows that perceived ease of use of social networks, perceived usefulness of social networks, perceived enjoyment from social network use, subjective norm, and user satisfaction were the main determinants that influence students' attitudes towards the use of social networks for collaborative learning. Additionally, the study found social networks as a useful tool for improving the academic performance of students in HEIs. We therefore envision that this study would influence policy, practice, and research on the use of social networks for teaching and learning in HEIs in the Global South.

Keywords Social networks · Collaborative learning · Higher education institutions · Teaching and learning · Educational technology

1 Introduction
The global call for digital innovations in education amid the pandemic has necessitated the need to enhance social network integration with current academic applications and other associated expansions. Research has shown that active, social, contextual, engaging, and student-owned educational experiences lead to deeper learning and understanding [1]. Social networking sites are being used by students to collaborate and share ideas about their academic activities as the pandemic lingers on. While some students use social network (SN) platforms to enhance and promote collaborative learning with colleagues, others are grappling with what to use to enhance collaborative learning [2]. Conversely, the frugality of online technologies in contemporary times poses several threats to students since safeguarding the privacy and integrity of their data is practically impossible [3, 4]. For instance, while teachers are concerned with using social network technologies to engage students in teaching and learning, students are apprehensive about the protection of their information assets on social network platforms [5, 6].

Collaborative learning is an approach to teaching and learning used by at least two or more people to achieve a common goal [7]. Collaborative learning helps develop a higher level of thinking, oral communication, self-management, and leadership skills. It also promotes student–faculty interaction and increases student retention, self-esteem, and responsibility. The emergence of Web 2.0 technologies has favoured the concept, which sets the tone for computing and collaborative engagement [8]. Conversely, this was difficult to achieve in the Web 1.0 era when the web and its content...
were static [9]. Web 2.0 incorporates intelligent, intuitive, and participatory "read-write" tasks where users are permitted to be both curators and consumers of digital content in real-time through a web browser [10]. This trajectory has been impressive with several signs of progress made to explore the affordances of SNs in the academic field and how these platforms could improve learning quality in HEIs [11]. Grounding on the technology acceptance model (TAM) and uses and gratification theory, this study aimed to unravel the determinants of using SNs for collaborative learning in the HEIs in Ghana.

2 Literature review

2.1 Study context—higher education institutions in Ghana

Ghana's tertiary education system is among the pioneering modern education in the West African sub-region [12]. Tertiary education in Ghana primarily focus on providing formal education to post-secondary graduates in diverse fields and disciplines [12]. As the fulcrum of growth in every economy, Ghana's tertiary education system has evolved from the pre-independent era to date under the regulations of the Ghana tertiary education commission (GTEC) [13]. Backed by the new Education Regulatory Bodies Act, 2020 (Act 1023), the GTEC is empowered to ensure the general effective, efficient and quality administration of tertiary education institutions and advance the application of scholarly knowledge through teaching and research using technology. Ghana currently has 304 accredited public and private tertiary institutions segmented into universities and university colleges, technical universities, colleges of education and professional institutions [14].

Given the above, Sasu [15] reports that there has been a corresponding increase in enrolment into tertiary institutions in Ghana. As of 2020, over 547 thousand students have enrolled in various tertiary educational institutions. The rising number stems from the growing need for enhanced education in a bid to attain the sustainable development goal in education. Yet, the accompanying funding and infrastructure to meet this development have not been forthcoming from government and relevant stakeholders amid the rising cost of tertiary education in Ghana [13]. Amid the infrastructure deficit, the COVID-19 pandemic also came to aggravate the situation. For instance, [16] aver that the pandemic disrupted the already fragile teaching, learning and administration of institutions in Ghana. This disruption ignited the inertia and transitioned a new era of online teaching and learning. Soon after the pandemic started, many HEIs adopted variants of e-learning infrastructure in response to the disruption [17]. Notable among these platforms were Moodle and Zoom.

Nonetheless, a gap existed with the e-learning platform relative to scalability. Moreover, there was the need to integrate existing e-learning platforms with SN platforms such as YouTube and WhatsApp to augment access to teaching and learning. This was apparent because of the rising dependence on SNs by learners at the time of the lockdown. A recent study by Kolog et al. [18] submitted that this trajectory caused a paradigm shift from traditional teaching and learning to collaborative teaching and learning in the global south. Given the fact that, the transition has come with myriads of setbacks, few institutions in Ghana found it prudent to operationalize online teaching and learning to stem the impact of the pandemic on academic activities [18, 19]. Thus, this study explores how SNs were employed in collaborative learning for students in HEIs during the peak of the COVID-19 pandemic.

2.2 Social network for collaborative learning

The proliferation of social media platforms and the gradual surge in usage have led to an increasing interest in research in this area [20, 21]. The use of social networking platforms has become a common practice for many internet users to express attitudes, opinions, and sentiments about real-world events (such as pandemics) while engaging in virtual interactions [22]. According to a Statista report, the global subscription to social networks as of 2020 was estimated to be over 3.6 billion people [23]. This is occasioned by the dominance of Web 2.0 with its superflux dynamism, interface and integrated intelligence over Web 1.0 [24]. Yadav and Sabhavat [23] further reported that the web has become attractive due to numerous intuitive social media plug-ins. Greenhow and Lewin [25] aver that students use social networks for interactivity particularly in a social environment. In recent times, for instance, students in higher education institutions (HEIs) have gradually shifted their attention to social networks for academic enhancement partly due to the exigencies of the COVID-19 pandemic [26].

Fundamentally, a social network (SN) is classified as a web-based technology that assists users to chat, participate, share and distribute ideas, thoughts, information and content in an extremely collaborative virtual environment [27]. Social networking platforms often come with a set of technological tools that cater to a wide range of interests and practices. The uses of conventional social networking platforms, such as WhatsApp, WeChat, Viber, Facebook, Google Hangout, Dropbox, Twitter, LinkedIn and YouTube, have become pervasive among students mainly for peer-to-peer communication [28]. As of March 2020, about 43.73% of Ghanaians used Facebook, 25.84% used Twitter, 15.31% used Pinterest, 11.17% used Instagram, 3.71%
used YouTube, 0.1% used LinkedIn, 0.03% used Vkontakte, 0.06% used Tumblr and Reddit [29]. Besides, amid the COVID-19 pandemic, students are using available learning technologies and social networking platforms to improve their learning and collaborative capabilities [30]. Conversely, prior to the outbreak of the COVID-19 pandemic, students from many African countries leveraged the capabilities of SNs mainly for other purposes such as entertainment and socialization (Linblom, Kolog & Sutinen, 2021).

In their study, [31] submit that SN platforms facilitate collaborative activities such as knowledge sharing among students. The semblance of such collaborative learning activities includes classroom discussions, seminars or lectures, or year-long research projects. Collaborative learning may be articulated in several forms by instructors of various teaching backgrounds, but the nexus is integrating assumptions about students and their learning cycle [32]. Beard and Wilson [33] suggest that learning is impacted by the circumstances and purpose in which it is adopted. Students are drenched in challenging moments and questions through collaborative learning activities. For instance, collaborative learning activities mostly start with issues for which students must rationalize appropriate realities and ideas to apply [26]. Rich contexts such as social networks in collaborative learning have challenged some students to practice and create a higher sense of reasoning and problem-solving skills [34]. Through collaborative learning, students can present several perspectives in the classroom with different experiences, learning styles, encounters, and ambitions. According to the literature, when students explore their classroom learning together, teachers promptly get an idea of how they are learning through their contributions to the class [35].

Extant studies (e.g. [36] have called for the inclusion of virtual learning in every quarter of students’ learning in higher education. The involvement of students, lecturers, and faculty members makes an overwhelming difference in student performance in higher education. This involvement allows students to build mutual relationships with staff, courses and learning directions. Students are recognized as having inevitable encounters through the involvement of collaborative activities. For example, developing the ability to tolerate or resolve differences is essential to living in a community, reaching an agreement that respects all group members, and ensuring that others do it. However, developing these values and skills often boils down to student life on campus and one-to-one learning. Collaboration, networking, and leadership development are real goals in the classroom, not just outside the classroom. In a meaningful democracy of students’ learning, the higher education system must foster the habits of students’ participation and involvement in a large community. This is because collective learning has helped students activate their voices in shaping their thoughts and values and sharpening their hearing when they hear others [30]. Dialogue, discussion, and consensus-building are important topics in both collaborative learning and civic life.

Based on the relevance of SNs for collaborative learning and the context of this study, this paper seeks to respond to the following questions: 1) How are social networks used for collaborative learning amid the COVID-19 pandemic in institutions of higher learning? b) What are determinants for motivating the use of social networks for collaborative learning in the institutions of higher learning? and c) What are the benefits of using social networks for collaborative learning in the institutions of higher learning?

3 Methodology

3.1 Theory

This study is grounded on the technology acceptance model (TAM) and the uses and gratification (U&G) theory. These theories were leveraged to determine the factors that influence social network use for collaborative learning in the institutions of higher learning in Ghana. TAM, developed by Davis [37], shows how users come to accept and use new technology [38]. Perceived ease of use and perceived usefulness are the two main constructs that influence a user’s decision to use new technology [37]. The TAM model suggests that the attitude towards using technology influences the behavioural intention to adopt and use technology. The three constructs explain what drives a user to accept new technology: perceived ease of use, perceived usefulness, and intention to use the technology. Davis [37] hypothesized that behavioural intention drives users to adopt and use new technology. Users’ attitudes influence their behavioural intentions towards the use of a system. Davis [37] modified his conceptual model to propose a new technology acceptance model by drawing on prior work by Fishbein and Ajzen [39] who developed the Theory of Reasoned Action. Davis [37] assumed that the user’s attitude towards the system was a determining factor in the use or rejection of the system.

The theory of U&G provides a way to understand why and how individuals actively seek specific media to meet their specific needs [40]. The U&G theory tries to clarify which psychological or social desires influence individuals to choose certain content and media channels and the resulting attitudinal and behavioural outcomes [41]. This study adopts the hedonic construct from U&G theory. The previous literature refers to hedonic gratification as a delight from a joyful experience. Thus, the aesthetics of deviation, rest, enjoyment, and time spent [42–44]. Prior studies (e.g. [21, 43–48]) used similar variables of gratification, such as escapism, enjoyment, time passing and intrinsic enjoyment. Ha et al. [46] in their study found that hedonic gratifications
have a direct influence on users' attitudes towards mobile SN use in Korea.

According to Fishbein and Ajein (1975, p. 302), a subjective norm is “a user’s perception that people who are close and important to you think you should or should not behave the way you do concerning the adoption and use of a new technology”. Following this, Venkatesh and Davis [49] described subjective norms as the resultant social influence and social pressure which influence why a person behaves in a specific way. In this study, we argue that individuals' behaviour is influenced by their immediate surroundings. Thus, we adopt the subjective norm construct from Fishbein and Ajein (1975). Prior studies have shown that subjective norm is the pre-stage that anticipates behavioural intention [49, 50] even though [51] suggested a contrary view in their study. According to the latter, peers, authorities or leaders, and other social influences have no impact on users' behavioural intentions or attitudes to adopt and use new technology. Figure 1 illustrates the conceptual framework of the proposed research.

### 3.2 Hypothesis development

#### 3.2.1 Perceived ease of use, attitude, usefulness influence on behavioural intention

The degree of effort required to use a particular system is defined as the perceived ease of use. This definition is driven by the fact that ease simply means "freedom from difficulty or much effort". Karoui et al. state that ease of use of a system implies that students use a particular social network feature easily and manage or manipulate their content without much effort or assistance. The TAM assumes that students are most likely to use a new technology when they believe that the intended purpose of using the technology would easily improve their academic performance. To this end, [52] developed a modified TAM model that incorporates synchronicity, involvement, and user flow to predict the attitude and intention to use new technology. Social networking sites provide a variety of opportunities for users to facilitate communication, information sharing, collaboration, and entertainment. In this study, usefulness is referred to as the perception to believe that using a particular system enhances the performance of the user's outcome [53]. The TAM postulates that students are likely to adopt and use new technology for collaborative learning whenever they believe it would help them improve their academic performance. According to Boateng et al. [54], perceived usefulness has a direct influence on behavioural intention. Hence, we hypothesize the following:

H1: There is a significant relationship between perceived ease of use and attitude towards the use of social networks.

H2: There is a significant relationship between perceived ease of use and behavioural intention to use social networks.

H3: There is a significant relationship between perceived usefulness and attitude towards the use of social networks.

H4: There is a significant relationship between perceived usefulness and behavioural intention to use a social network.

#### 3.2.2 Perceived enjoyment, attitude, subjective norms influence on behavioural intention

Perceived enjoyment (PE) is the degree to which the use of technology is considered enjoyable by the user in addition to any expected performance consequences [55]. In other words, perceived enjoyment is the passion and excitement derived from using an online technology. Van der Heijden...
3.2.3 Behavioural Intention, attitude, and user satisfaction to use social networking sites

Students’ intention to use social networks for collaborative learning is a major motive in integrating information systems. An intention to use a system is a result of the attitude towards individual user behaviour and subjective norms (perceived control), conferring with the tenets of the Theory of Reasoned Action (TRA) [59]. According to Akman and Mishra [60], perceived enjoyment is believed to be the paramount user post-adoptive intention of a system that leads to an increased level of user satisfaction and continued use of the system. In reference to the work of [61], students who enjoy or feel comfortable with new technologies interact with the system more positively and therefore have a high behavioural intention to use it. Emanating from this discussion, we hypothesize the following:

H5: There is a significant relationship between perceived enjoyment and attitude towards social network usage.
H6: There is a significant relationship between perceived enjoyment and behavioural intention to use social networks.
H7: There is a significant relationship between the intention to use social networks and subjective Norms.

3.2.4 Relationship between Behavioural intention, User satisfaction and learner outcome

One of the needs to study students’ online interaction among themselves is to highlight whether there are different cultural influences on social media engagement among students from different cultural ideologies [62]. As stipulated by studies [37, 63–64], the most significant variables which derive users’ adoption and satisfaction of any new technology are the perceived usefulness and perceived ease of use due to the observation that these variables are indicators of students’ satisfaction with SNs. The previous literature revealed that students’ engagement on social media greatly influences their academic performance, cognitive skills, and skill development [65, 66]. Dumpit and Fernandez [67] assert that the use of social media use in institutions of higher learning improves interaction and access to education. In addition, Stathopoulou et al. [68] stated that social networks in the educational realm bridge the communication gap between students and instructors. Given that SNs are for entertainment and learning purposes, tertiary students are likely to use these applications for their academic indulgences. Hence, we hypothesize the following:

H10: There is a significant relationship between behavioural intention to use social networks and user Satisfaction.
H11: There is a significant relationship between students’ satisfaction and learners’ outcomes.

3.3 Sampling and data collection

Based on the study’s objectives, we limited the sample to students of HEIs in Ghana. The questionnaire design was guided by the study’s framework in Fig. 1. The questionnaire was divided into two sections: Part A explored general information about the participants, and Part B contained questions on the determinants of collaborative learning. Students were conveniently sampled from the HEIs in Ghana to respond to the questions. The questionnaire was designed to collect both open and closed-ended questions. While the open-ended questions touched on the personal information of the participants, the close-ended questions were on a 5-point Likert scale (1-Strongly agree to 5-Strongly disagree). Ethically, the selected participants were made to give their consent before the data were collected. The study’s objectives were captured on the questionnaire, requesting the participants to be abreast before responding. A pre-test was conducted among 46 students from different HEIs to ascertain the validity of the questions. The final questionnaire was digitally administered to students and a total of 360 students from different HEIs in Ghana responded.
3.4 Method of data analysis

Data analysis was carried out using SmartPLS software for structural equation modelling (SEM). SEM is a multivariate statistical analysis technique that is used to analyse structural relationships. This technique is a combination of factor analysis and multiple regression analysis, and it is used to analyse the structural relationship between measured variables and latent constructs. While SEM encompasses the variance-based and co-variance-based techniques, this study employed the variance-based (partial least square) technique where SmartPLS was used. The reason for this technique is its robustness, predictive component, and flexibility to assess both the measurement and structural models. With the use of SmartPLS, the strength of the indicators in each of the constructs (measurement model) and among the constructs (structural model) was assessed. Despite assessing the inferential statistics with the SmartPLS, the descriptive component of the data was computed. The expectation-maximization algorithm, a clustering technique, was used to handle all the missing data to improve the quality of the analysis. The demographic analysis was analysed with SmartPLS-SEM.

3.5 Demographic information

Table 1 summarizes the profile of the respondents. Out of the 360 samples, the majority of the participants were male (61.5%). Students prefer to use mobile phone to learn and to collaborate in academic activities due to their portability. Hence, of the total number of the participants who use mobile phones, only 72.6% of them use android-based-phones. Side portability, this could be attributed to the ease (cost) of access to android phones as compared with the iPhone. In addition, the most frequently used social networking site for collaborative learning was YouTube (42.38%), while the least used platform was Twitter. The data collected also revealed that the majority of respondents have been using social networks for less than 6 years. Further, most students revealed that they spend less than 5 h daily on social networking sites.

| Category                                | Variables   | Frequency (N = 361) | Percentage (%) |
|-----------------------------------------|-------------|---------------------|----------------|
| Gender                                  | Male        | 222                 | 61.5           |
|                                         | Female      | 139                 | 38.5           |
| Qualification                           | Diploma/HND | 225                 | 62.3           |
|                                         | Bachelor degree | 124              | 34.4           |
|                                         | Master degree  | 12                  | 3.3            |
| Level of current study                  | Year 1      | 128                 | 35.5           |
|                                         | Year 2      | 102                 | 28.3           |
|                                         | Year 3      | 64                  | 17.7           |
|                                         | Year 4      | 67                  | 18.5           |
| Device used for learning                | Android Phone | 262               | 72.6           |
|                                         | Apple Phone   | 56                  | 15.5           |
|                                         | Computer     | 34                  | 9.4            |
|                                         | Tablet       | 9                   | 2.5            |
| Social networking site used for learning| YouTube     | 153                 | 42.4           |
|                                         | Facebook     | 8                   | 2.2            |
|                                         | WhatsApp     | 137                 | 38.0           |
|                                         | LinkedIn     | 22                  | 6.1            |
|                                         | Twitter      | 1                   | 0.3            |
|                                         | Others       | 40                  | 11.1           |
| Duration of using social networks       | Less than 2 years | 110              | 30.5           |
|                                         | Between 2–5 years  | 148             | 41.0           |
|                                         | Between 5–10 years | 72               | 19.9           |
|                                         | Above 10 years | 31                  | 8.6            |
| Time spent on social networks for learning daily | Less than 5 h | 174           | 48.2           |
|                                         | Between 5–10 h | 137                | 38.0           |
|                                         | Between 10–15 h | 26               | 7.2            |
|                                         | Above 15 h   | 24                  | 6.6            |
4 Results

4.1 Measurement model assessment

4.1.1 Indicators reliability

The reliability of an indicator is the degree to which a variable or set of variables is consistent with what it intends to measure [69] p.18). Loadings of reflective indicators are monitored to check the reliability of the indicator. According to Hair et al. [70], loading indicators of 0.70 and above are accepted because they provide acceptable reliability of the constructs. Hence, in this study, the variable PEJ2 was removed since its indicator was found to fall below the acceptable threshold. A subsequent rerun of the data on the SmartPLS_SEM showed all indicators were significantly loaded with the corresponding hidden variables. An indication that all variables were good at measuring the latent variables. After achieving a good measuring variable, we extracted the results to evaluate the measurement and structural models. Figure 1 presents the resultant loading of the indicators (Table 2 and Fig. 2).

4.1.2 Internal consistency and convergent validity

The internal consistency was measured using the Cronbach Alpha. According to Taber [71], the Cronbach’s alpha value should not fall below 0.70. In other words, values below the minimum threshold do not show a good outcome for the model. As indicated in Table 3, all the variables yielded a satisfactory Cronbach’s alpha. Nonetheless, the reliability and accuracy of Cronbach’s alpha values have come under criticism since the average values of the elements are not extracted [69, 70]. Therefore, composite reliability was suggested as an alternative to assessing indicator reliability [72]. In composite reliability, the highest values of items represent a higher level of reliability and vice versa. Researchers considered reliability values between 0.60 and 0.70 as acceptable, values between 0.70 and 0.90 as good indicators, and values exceeding 0.95 as problematic because values

| Table 2 Cross-loadings |
|------------------------|
| ATT | BI | CLO | PEJ | PEOU | PU | SJN | US |
| ATT1 | 0.852 | 0.496 | 0.435 | 0.485 | 0.518 | 0.635 | 0.416 | 0.503 |
| ATT2 | 0.895 | 0.524 | 0.471 | 0.512 | 0.523 | 0.609 | 0.464 | 0.544 |
| ATT3 | 0.820 | 0.569 | 0.443 | 0.547 | 0.482 | 0.518 | 0.437 | 0.511 |
| BI1 | 0.450 | 0.780 | 0.436 | 0.578 | 0.428 | 0.503 | 0.404 | 0.491 |
| BI2 | 0.541 | 0.861 | 0.496 | 0.629 | 0.452 | 0.542 | 0.504 | 0.565 |
| BI3 | 0.540 | 0.879 | 0.558 | 0.573 | 0.478 | 0.570 | 0.473 | 0.660 |
| BI4 | 0.560 | 0.871 | 0.555 | 0.595 | 0.436 | 0.591 | 0.547 | 0.727 |
| CL1 | 0.426 | 0.485 | 0.845 | 0.365 | 0.372 | 0.423 | 0.543 | 0.567 |
| CL2 | 0.478 | 0.562 | 0.907 | 0.496 | 0.453 | 0.551 | 0.498 | 0.618 |
| CL3 | 0.487 | 0.556 | 0.896 | 0.457 | 0.481 | 0.546 | 0.441 | 0.601 |
| PEJ1 | 0.469 | 0.604 | 0.362 | 0.816 | 0.544 | 0.624 | 0.372 | 0.471 |
| PEJ2 | 0.547 | 0.542 | 0.385 | 0.835 | 0.473 | 0.484 | 0.324 | 0.436 |
| PEJ4 | 0.524 | 0.656 | 0.467 | 0.870 | 0.499 | 0.545 | 0.415 | 0.550 |
| PEU1 | 0.478 | 0.441 | 0.474 | 0.468 | 0.824 | 0.596 | 0.297 | 0.482 |
| PEU2 | 0.522 | 0.367 | 0.343 | 0.448 | 0.811 | 0.511 | 0.276 | 0.395 |
| PEU3 | 0.345 | 0.479 | 0.352 | 0.521 | 0.747 | 0.486 | 0.223 | 0.372 |
| PEU4 | 0.528 | 0.396 | 0.398 | 0.475 | 0.795 | 0.600 | 0.281 | 0.421 |
| PU1 | 0.564 | 0.526 | 0.531 | 0.512 | 0.526 | 0.802 | 0.452 | 0.572 |
| PU2 | 0.592 | 0.546 | 0.520 | 0.546 | 0.621 | 0.858 | 0.360 | 0.540 |
| PU3 | 0.513 | 0.511 | 0.371 | 0.517 | 0.515 | 0.776 | 0.263 | 0.481 |
| PU4 | 0.598 | 0.528 | 0.474 | 0.531 | 0.556 | 0.832 | 0.412 | 0.530 |
| PU5 | 0.519 | 0.540 | 0.437 | 0.533 | 0.594 | 0.795 | 0.295 | 0.497 |
| SN1 | 0.420 | 0.418 | 0.407 | 0.418 | 0.266 | 0.345 | 0.761 | 0.453 |
| SN2 | 0.299 | 0.373 | 0.435 | 0.311 | 0.183 | 0.246 | 0.790 | 0.374 |
| SN3 | 0.454 | 0.541 | 0.457 | 0.412 | 0.324 | 0.384 | 0.812 | 0.470 |
| SN4 | 0.419 | 0.452 | 0.454 | 0.355 | 0.273 | 0.388 | 0.783 | 0.432 |
| US1 | 0.514 | 0.661 | 0.513 | 0.501 | 0.427 | 0.568 | 0.418 | 0.870 |
| US2 | 0.530 | 0.672 | 0.613 | 0.557 | 0.505 | 0.584 | 0.467 | 0.889 |
| US3 | 0.507 | 0.519 | 0.597 | 0.428 | 0.409 | 0.492 | 0.533 | 0.793 |

Bold implies the highest coefficient of the construct loading
above 0.95 are more than necessary and therefore cause the reliability of the model to decline [73]. Apart from the composite reliability, the Rho_A is also proposed as a good alternative for measuring reliability accuracy in the SEM-PLS model [74]. In the Rho_A, variables with values of 0.70 and above are recommended for inclusion and acceptance. Convergent validity is the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs ([69]. The outer loadings and the average variance extracted (AVE) are used to determine the convergent validity [75]. As indicated in Table 3, the AVE values are beyond 0.5, which implies a satisfactory convergent validity.

### 4.1.3 Discriminant validity

Discriminant validity is the extent to which a construct is truly distinct from other constructs by empirical standards [76]. Discriminant validity can be assessed by computing Fornell-Larcker, cross-loadings and heterotrait–monotrait ratio (HTMT). Although each of the measures has its weaknesses, researchers have advocated the use of HTMT as a measure of discriminant validity. HTMT is the mean value of the item correlations across constructs relative to the geometric mean of the average correlations for items measuring the same construct [76]. Fornell-Larcker criterion [77] was unable to address variables where their loadings differ slightly (i.e. between 0.650 and 0.850). HTMT brings forth what true correlations between two constructs are when they are perfectly reliable (measured). Unlike Fornell-Larcker criterion, HTMT can provide rates between 97 and 99% which are higher sensitive rates than those of the Fornell-Larcker criterion rates which are between 0.00% and 20.82% according to [78] (Table 4).

### 4.2 Structural model assessment

#### 4.2.1 Assessing multicollinearity statistics

To assess the inner structure of the model, we explored any collinearity issues with the predictor variables. Multicollinearity exists when two or more indicators are involved in correlation [79]. In collinearity, if two or more formative
indicators with the same values are entered into the same block of indicators, they are perfectly correlated. Variance inflation factor (VIF) was computed to ascertain the issues of collinearity. The issues of high levels of collinearity are critical because they affect the estimation of weights and the statistical significance of formative indicators. To avoid collinearity issues, Hair et al. [80] have proposed a minimum threshold of VIF of 5 or less. From Table 5, there are no collinearity issues since its values are all within the minimum threshold proposed by prior studies.

4.2.2 Assessing structural model path coefficients

The hypothesized relationships among constructs in the PLS-SEM analysis are referred to as the path coefficients. The standardized values of the path coefficients usually fall within the boundary of −1 and +1. The constructs estimated path coefficient values which are approximate to 1 have high positive correlations and the reverse is usually statistically significant but weaker in their relationships. The bootstrapping helps to achieve both the $t$ values and the $p$ values for

| Hypothesis | Path | Std_beta ($\beta$) | Std_Error | T_Statistics | Interpretation |
|------------|------|--------------------|-----------|--------------|---------------|
| H1         | PEOU $\geq$ ATT | 0.181              | 0.051**    | 3.197        | Supported     |
| H2         | PEOU $\geq$ BI | $-$0.010           | 0.053**    | 0.188        | Not Supported |
| H3         | PU $\geq$ ATT | 0.453              | 0.072**    | 6.359        | Supported     |
| H4         | PU $\geq$ BI | 0.201              | 0.073**    | 3.054        | Supported     |
| H5         | PEJ $\geq$ ATT | 0.168              | 0.061**    | 2.633        | Supported     |
| H6         | PEJ $\geq$ BI | 0.398              | 0.065**    | 7.443        | Supported     |
| H7         | SJN $\geq$ BI | 0.250              | 0.054**    | 4.341        | Supported     |
| H8         | ATT $\geq$ BI | 0.133              | 0.057**    | 5.094        | Supported     |
| H9         | ATT $\geq$ US | 0.255              | 0.055**    | 2.340        | Supported     |
| H10        | BI $\geq$ US | 0.569              | 0.059**    | 10.526       | Supported     |
| H11        | US $\geq$ CLO | 0.675              | 0.044**    | 15.906       | Supported     |

$\beta$ denotes the path coefficient; $t$ denotes two-tailed $t$-statistics at **0.05 Significant level
all the path coefficients [81]. After the bootstrap, if the t values are greater than the critical value, it is suggested that the coefficient has a significant level of reduced errors in the model. Note that, the study used the t value to measure the effect of each hypothesis based on the 1.65 threshold value as shown in Table 6.

Specifically, the observed relationship between hypotheses PEOU ($\beta = 0.181$, $t = 3.197$), PU ($\beta = 0.453$, $t = 6.359$) and PEJ ($\beta = 0.168$, $t = 2.633$) had a statistical relationship with attitude to use SNs for collaborative learning. This implies that the hypotheses H1, H3 and H5 are accepted. Other positive predictors [PU ($\beta = 0.201$, $t = 3.054$), PEJ ($\beta = 0.398$, $t = 7.443$), SJN ($\beta = 0.250$, $t = 4.341$) and ATT ($\beta = 0.133$, $t = 5.094$)] were significantly related to behavioural intention to use SN for collaborative learning. This therefore supports the hypotheses H4, H6, H7 and H8. However, H2 was not supported since the direct effect between PEOU and BI did not show any significant relationship ($\beta = -0.010$, $t = 0.188$). The study further sought to examine the relationship between some latent variables and user satisfaction. It emerged that ATT and BI had a significant relationship with user satisfaction at ($\beta = 0.675$, $t = 15.906$) in support of hypothesis H11.

### 4.2.3 Coefficient of determination ($R^2$ value)

The $R^2$ values are ranged between 0 and 1. The higher the value, the higher the predictive accuracy and vice versa. Due to the complexity of some models and the diverse research disciplines, it is difficult to provide standardized acceptable rules for $R^2$. However, scholars such as Hair et al. [82] and Henseler et al. [83] described $R^2$ values of 0.75, 0.50, and 0.25 for endogenous variables as significant, moderate, and weak, respectively, and recommended researchers to consider 0.75 values or above. Chin (1998) in the discipline information system research also considered $R^2$ values of 0.190, 0.333, and 0.670 as weak, moderate, and substantial, respectively (Table 7).

### 4.2.4 Model fit and effect size ($f^2$ value)

The Standardized Root Mean Squared Residual (SRMR) criteria were used to assess the goodness of fit of the model in this study. With the SRMR rule of thumb, the lower the value, the more perfect the model is fit and vice versa. According to [84], SRMR values lower than 0.10 or 0.08 are acceptable as the best fit of a model and the reverse indicates the absence of fitness. In the forgoing, this current study model is well fitted considering the values in Table 6 where the SRMR value of 0.087 is within the threshold (Table 8).

The effect size ($f^2$) is used to evaluate the impact of change in the value of $R^2$ when a specific construct of exogenous variables in the model is being omitted. Cohen (1988) proposed that $f^2$ values from 0.02 to 0.150 have a weak effect, 0.150 to 0.350 has a medium effect, and values above 0.350 have a large effect on the model (Table 9).

### 4.2.5 Assessing the predictive relevance ($Q^2$ value)

Stone-Geisser’s ($Q^2$) measure has been promoted to examine the predictive relevance of the data [85, 86]. Predictive relevance occurs when the PLS-SEM path accurately predicts data that is not used in the model estimation. The $Q^2$ is a criterion of predictive accuracy in the model. According to Hair et al. [80]) $Q^2$ values greater than zero for a specific reflective endogenous latent variable indicate the path model’s predictive relevance for a particular dependent construct. If the resulting values of $Q^2$ are above 0,

| Constructs | Attitude | BI | CLO | US |
|------------|----------|----|-----|----|
| Perceived ease of use | 0.026 | 0.000 |   |    |
| Perceived enjoyment | 0.059 | 0.164 |   |    |
| Perceived usefulness | 0.167 | 0.051 |   |    |
| Subjective norm | 0.103 |   |    |    |
| User satisfaction |   | 0.836 |    |    |

Table 8 Goodness of fit (SRMR criterion)

| Constructs | Original sample (O) | Sample mean (M) | 95%   | 99%   |
|------------|---------------------|-----------------|-------|-------|
| Saturated model | 0.061 | 0.04 | 0.045 | 0.048 |
| Estimated model | 0.087 | 0.048 | 0.057 | 0.062 |

Table 9 Assessing effect size using $f$-square values
5 Discussion and implications

5.1 Discussion

This study has revealed that social networks potentially enable collaborative learning in HEIs by providing ubiquity, accessibility and enhancement of learning outcomes. Apparently, extant studies such as [65, 66], Dumpit & Fernandez, 2017a) affirmed this assertion. According to Stathopoulou et al. [68], SNs help students and instructors communicate more effectively which ultimately improves learning methodologies and cognition. Additionally, relative to the determinants of SNs use for collaborative learning (Research question 2), this study found students’ attitudes and intention to use social networks for collaborative learning to be strongly influenced by the perceived ease of use, perceived usefulness, perceived enjoyment, and subjective norm which resulted in the confirmation of hypotheses H1, H3, H4, H5, H6 and H7. These findings are supported by the works of Lorenzo-Romero et al. [87] and Shin [88] who found a similar relationship. In addition to this finding, students’ attitudes influence their intentions to use SN for collaborative learning in HEIs. This affirms a prior study by Yue et al. [89] who revealed that the attitude of users is the motive behind the behavioural intention to use new technology. It can therefore be concluded that where students exhibit positive behaviour with the use of SNs in the context of education, their decision to use them for collaborative learning becomes high.

Darko-Adjei [90] assessed the impact of social media on students’ learning performance in Ghana. The study found social media as a destructive tool to students’ learning outcomes, and that, privacy issues were the main challenges confronting students when using social media. This finding springboards the relevance of this study as it investigated the determining factors for using SNs for collaborative learning in HEIs in Ghana. Thus, perceived ease of use of SNs is a major determinant of students’ attitudes towards collaborative learning as indicated in Table 6 in this study. Similarly, Alhassan et al. [75] and Boateng et al. [54] found a significant attitudinal influence on the perceived ease of use of technology where SNs are inclusive. This implies that students’ attitude towards using SNs largely depends on the flexible nature of social networking sites for collaboration. The ease with which users can navigate through SNs, as well as the aesthetic and functional capabilities of SN platforms are all factors to consider. Given the above, social network developers are better informed on the need to involve end-users in the developmental process. End-users’ involvement in artefact development motivates the use and acceptance of that technology [91], especially when they are made to be co-creators. That notwithstanding, it also emerged from this study that students’ intention to use SNs for collaborative learning is not influenced by the ease of use of SNs, hence, the rejection of hypothesis H2 contrary to the initial proposition. This, therefore, contradicts the findings of Phua et al. [92] who revealed that perceived usefulness and perceived ease of use are the two main factors that influence users’ intention to adopt new technology. The discrepancy could be attributed to the varied context of study.

Furthermore, the usefulness of SNs for collaborative learning was found to have a significant influence on the attitudes and intentions to use SNs. This implies that students who exhibit attitudinal tendencies and intentions to use SNs for collaborative learning do so by first examining their usefulness in academic orientation. It is, however, apparent that the effectiveness of collaborative learning in HEIs highlights the usefulness of SNs as affirmed by Boateng et al. [54] who revealed that perceived usefulness directly influences the behavioural intention of users towards using a technology. Despite the usefulness of using SNs for collaborative learning, perceived enjoyment is influenced by students’ attitudes and intentions.

Another major finding of this study is that the social influence (subjective norms) of students, either through their peers or teachers, had a strong influence on their intentions to use social networks for collaborative learning. This finding affirms prior studies where the subjective norm was found as a pre-stage that anticipates the behavioural intention of users to use a system [49, 50]. Abu-Al-Aish and Love [93] found that social norms from peers, teachers through group assignments and parents influence the decision of students to use social networks for collaborative learning. Similarly, [63, 2] found a significant influence of peers on students’ academic performance after exploring life stories with natural language processing and machine learning techniques.
It is apparent in Table 6 that users’ attitudes and behavioural intentions to use SNs for collaborative learning were influenced by the satisfaction that the students anticipated. This includes the use of social networks to improve academic outcomes and performance. Thus, affirming hypothesis H11. In response to the benefits of using SNs for collaborative learning, it emerged that, using social networks collaboratively helps them to better understand their course content than traditional teaching and learning. Peers and teachers can collaborate and share ideas remotely and anytime provided there is a stable internet connection as corroborated by [2]. In a similar vein, this study found the use of social networks for collaborative learning to significantly influence students’ academic performance. The work of Owusu-Acheaw & Larson [66] also affirms this finding by revealing that students’ engagement on social media has a significant influence on their academic performance, cognitive skills, and skill development. A study by [94] on user acceptance of computer-supported collaborative learning with SN awareness generally corroborated the findings of this study. Employing the unified theory of use and acceptance of technology, the SNs mechanism significantly strengthened the effect of social influence on behavioural intention to use the SNs for collaborative learning among undergraduate students in China [94].

Given the increasing development of SN use in diverse economic fields, its application in education has deepened due to the growth in the new media, especially during the recent COVID-19 pandemic. Globally, SNs are emerging technologies in the educational sector. For this reason, there have been calls for constructive studies to unearth more findings that support the existing literature and theories for proper integration [26]. In this study, we were motivated by this call to proffer nuanced understanding of the determinants of SNs use for collaborative learning in HEIs. In respect of the transient nature of educational infrastructure in the Global South, researchers need to unearth resilient tools to help fortify the already fragile educational infrastructure amid the pandemic [18]. This study has therefore set the pace and is arguably the first to explore the determinants of SN use for collaborative learning from the perspective of students in the HEIs in Ghana in the African context.

### 5.2 Implications

This study has some implications for practice, research and policy. The implications are far-reaching given the necessity of SNs in collaborative learning occasioned by the unfolding COVID-19 pandemic. The study has set the pace for a deeper understanding of the drivers of collaborative learning by leveraging the capabilities of SNs. The use of social networks in the educational sector will help to strengthen the communication gaps among students and staff in their pursuit of continuous academic activities, especially amid the COVID-19 pandemic. This study affirms that students’ attitudes and behavioural intentions to use SNs for collaborative learning determine their level of satisfaction. This is principally outstanding in resource constraints economic settings such as Africa where SN tools offer an array of opportunities for management to leverage to coordinate learning activities. In effect, this study courts the attention of the management of HEIs to be wary of the choice of students relative to SN applications in their learning exploits. This study is to equip the management of HEIs to make informed decisions in their selection of SN tools for enhancing students’ learning. That said, management will be mindful of the factors that drive learners to use SN for collaborative learning. These factors are key in promoting and developing SN tools for multiple academic activities. As emerged from this study, developers of SN tools will be informed to embrace attributes such as user-friendliness and useful content to make learning exciting. Thus, institutions that intend to integrate social networks into their learning curriculum should understand the nature and determinants of SN usage by students for learning.

We implore the management of HEIs to be abreast with the current issues in contemporary educational technologies. In terms of policy, an enabling information and communication technology environment must be created in the various institutions of higher learning to motivate students and other users to adopt and use social networks for collaborative learning. Essentially, institutions that intend to integrate social networks into their learning curriculum will be guided by the findings of this study. Having acquired some fundamental understanding of the antecedents and determinants of social network usage by students for learning, HEIs can effectively incorporate SNs-enabled collaborative learning tools that were inaccessible, especially in the Ghanaian educational curriculum. In the process of adoption and incorporation by institutions to improve their teaching and learning, preference will be given to attributes such as the ease of use of the sites, their usefulness, the excitement they provide, and the satisfaction level of the users. To the best of our knowledge, this study is the first of its kind to explore the determinants of using social networks for collaborative learning in Ghana by integrating subjective norm constructs into TAM.

### 6 Conclusion

This study explored the determinants of SNs usage for collaborative learning among students in HEIs in Ghana. Grounding on TAM and U&G theory, the study explored the determinants of using SNs and the consequences on students’ academic performance. Essentially, the findings
affirm that ease of use, usefulness, excitement and subjective norms of using social networks have diverse consequences on users’ attitudes and behavioural intentions towards SN-enabled collaborative learning. These attributes chart a new pathway for further investigation into other divergent factors, perhaps not intended for only students but management alike in the future. These findings, though formative, will accelerate future studies on the adoption, implementation, and usage of SN for collaborative learning aimed at restructuring the integration of educational technologies in HEIs. Additionally, the study has revealed that, though students in the HEIs use social networks, these network sites have not been formally integrated into the students’ learning curriculums. Essentially, students use these sites for collaborative learning for group assignments, case studies, project works, study groups, class groups, among others. While we envision that this study will guide policy and practice in terms of the management of the educational sector in Ghana amid the COVID-19, we recommend future studies to explore the level of satisfaction and the challenges associated with using social networks for collaborative learning. Based on the findings, it is our recommendation that HEIs in the Global South find a restrictive way to integrate the use of SNs into their teaching and learning. This could be included by gamifying SNs to promote teaching and learning.

Acknowledgement This project received funding from the University of Ghana business school. Thus, we acknowledge the effort of the school in promoting scholarship.

Authors contributions P.K.B, E.A.K, E. A-D conceptualized the research idea. P.K.B worked on the questionnaire and collected the data. P.K.B and E.A.K developed the theory and performed the statistical analysis. E. A-D, E.A.K and S.B.E verified the analytical methods, E.A-D and S.B.E proofread and edited the paper and made recommendations for improvement. All authors contributed to the discussion of the results and contributed to the final drafting of the paper.

Funding This study received funding from the University of Ghana Business School

Data availability Data for this study are available on request.

Declarations

Competing interests We declare no conflict of interest and also competing interest.

References

1. Paul, A., Kundu, D.: Collaborative learning. Int. J. Engl. Learn. Teach. Skills 3(4), 2567–2576 (2021)
2. Kolog, E.A., Tweneboah, S.N.A., Devine, S.N.O., Adusei, A.K.: Investigating the use of mobile devices in schools: a case of the Ghanaian senior high schools. In Mobile Technologies and Socio-economic development in emerging nations. IGI Global (pp. 81–108) (2018)
3. Shah, M.A., Santandreu Calonge, D.: Frugal MOOCs: an adaptable contextualized approach to MOOC designs for refugees. Int. Rev. Res. Open Distrib. Learn. 20(5), 1–19 (2019)
4. Zacharis, N.Z.: A multivariate approach to predicting student outcomes in web-enabled blended learning courses. Internet High. Educ. 27, 44–53 (2015)
5. Greenhow, C., Galvin, S.: Teaching with social media: evidence-based strategies for making remote higher education less remote. Inf. Learn. Sci. 121(7–8), 513–524 (2020)
6. Köse, Ö.B., Doğan, A.: The relationship between social media addiction and self-esteem among Turkish university students. Addicta Turk. J. Addict. 6, 175–190 (2019)
7. Song, Y.: Improving primary students’ collaborative problem solving competency in project-based science learning with productive failure instructional design in a seamless learning environment. Educ. Tech. Res. Dev. 66(4), 979–1008 (2018)
8. Moseti, M.F.: Adoption of web 20 in learning management systems in universities in Nairobi: development of a UTAUT based model. United States International University-Africa, Kenya (2019)
9. Boman, M., Abdesslem, F.B., Forsell, E., Gillblad, D., Görnerup, O., Isacsson, N., Kaldo, V.: Learning machines in internet-delivered psychological treatment. Prog. Artif Intell. 8(4), 475–485 (2019)
10. McGrath, D.A.: Quantitative analysis for system applications: data science and analytics tools and techniques. Technics Publications, NJ (2018)
11. Agbo, F.J., Olawumi, O., Oyelere, S.S., Kolog, E.A., Olaleye, S.A., Agjie, R.O., Olawumi, A.: Social media usage for computing education: the effect of tie strength and group communication on perceived learning outcome. Int. J. Educ. Dev. Inf. Commun. Technol. 16(1), 5–26 (2020)
12. Atuahene, F., Owusu-Ansah, A.: A descriptive assessment of higher education access, participation, equity, and disparity in Ghana. SAGE Open 3(3), 215824013497725 (2013)
13. Acquah, A.: Higher Education Finance Between Ghana and the United States. Current Issues Comp. Educ. 23(1) (2021)
14. GTEC, (2022). Ghana Tertiary Education Commission. https://gtec.edu.gh/institution-category (Accessed: 12/10/2021)
15. Sasu, D.D. (2021). Number of tertiary students in Ghana 2005–2020, by type of education, Statista. https://www.statista.com/statistics/1180524/ number-of-students-in-tertiary-education-in-ghana/(Accessed: May 12, 2021)
16. Upoalkpajor, J.L.N., Upoalkpajor, C.B.: The impact of COVID-19 on education in Ghana. Asian J. Educ. Soc. Stud. 9(1), 23–33 (2020)
17. Sarpong, S.A., Dwomoh, G., Boakye, E.K., Ofosu-Adjei, I.: Online teaching and learning under COVID-19 Pandemic: perception of university students in Ghana. Eur. J. Interact. MultimeD. Edu. 3(1), e02203 (2022). https://doi.org/10.30935/ejmed/11438
18. Kolog, E.A., Egala, S.B., Amponsah, R., Devine, S.N.O., Sutinen, E.: COVID-19 pandemic: how can the lessons learnt contribute to the digital transformation of schools of tomorrow? Int. J. Technol. Enhanc. LearN. 14(2), 142–162 (2022)
19. Owusu-Fordjour, C., Koomson, C.K., Hanson, D.: The impact of COVID-19 on learning—the perspective of the Ghanaian student. Eur. J. Educ. Stud. 7(3), 89 (2020)
20. Kapoor, K.K., Tamilmani, K., Rana, N.P., Patil, P., Dwivedi, Y.K., Nerur, S.: Advances in social media research: past, present and future. Inf. Syst. Front. 20(3), 531–558 (2018)
21. Zhang, Y., Leung, L.: A review of social networking service (SNS) research in communication journals from 2006 to 2011. New Media Soc. 17(7), 1007–1024 (2015)
sentiment analysis. Electronic J. Inform. Syst. Eval. 21(1), 1–19 (2018)
64. Raza, S.A., Umer, A., Shah, N.: New determinants of ease of use and perceived usefulness for mobile banking adoption. Int. J. Electronic Cus. Relat. Manag. 11(1), 44–65 (2017)
65. Al-Rahmi, W.M., Zeki, A.M.: A model of using social media for collaborative learning to enhance learners’ performance on learning. J. King Saud Univ. Comput. Inform. Sci 29(4), 526–535 (2017)
66. Owusu-Acheaw, M., Larson, A.G.: Use of social media and its impact on academic performance of tertiary institution students: a study of students of Koforidua Polytechnic Ghana. J. Educ. Pract. 6(6), 94–101 (2015)
67. Dopathoulou, A., Siamagka, N-T., Christodoulides, G.: A multi-stakeholder view of social media as a supporting tool in higher education: An educator–student perspective. Eur. Manag. J. 37(4), 421–431 (2019)
68. Urbach, N., Ahlmann, F.: Structural equation modeling in information systems research using partial least squares. J. Inform. Technol. Theory Appl. 11(2), 5–40 (2010)
69. Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M.: When to use and how to report the results of PLS-SEM. European business review (2019).
70. Taber, K.S.: The use of Cronbach’s alpha when developing and reporting research instruments in science education. Res. Sci. Educ. 48(6), 1273–1296 (2018)
71. Purwanto, A.: Partial least squares structural equation modeling (PLS-SEM) analysis for social and management research: a literature review. J. Indus Eng Manag Res 2(4), 114–123 (2021)
72. Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., Kaiser, S.: Guidelines for choosing between multi-item and single-item scales for construct measurement: a predictive validity perspective. J. Acad. Mark. Sci. 40(3), 434–449 (2012)
73. Dijkstra, T.K., Henseler, J.: Consistent partial least squares path modeling. MIS Q. 39(2), 297–316 (2015)
74. Alhassan, M.D., Kolog, E.A., Boateng, R.: Effect of gratification on user attitude and continuance use of mobile payment services: a developing country context. J. Syst. Inform. Technol. (2020). https://doi.org/10.1108/JST-01-2020-0010
75. Sarstedt, M., Hair, J.F., Jr., Cheah, J.-H., Becker, J.-M., Ringle, C.M.: How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australas. Mark. J. AMJ 27(3), 197–211 (2019)
76. Fornell, C., Larcker, D.F.: Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18(1), 39–50 (1981)
77. Henseler, J., Ringle, C.M., Sarstedt, M.: A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43(1), 115–135 (2015)
78. O’Brien, R.M.: A caution regarding rules of thumb for variance inflation factors. Qual. Quant. 41(5), 673–690 (2007)
79. Hair, J.F., Jr., Hult, G.T.M., Ringle, C.M., Sarstedt, M.: A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications, New York (2021)
80. Sarstedt, M., Hair, J.F., Ringle, C.M., Thiele, K.O., Gudergan, S.P.: Estimation issues with PLS and CBSEM: where the bias lies! J. Bus. Res. 69(10), 3998–4010 (2016)
81. Hair, N.L., Hanson, J.L., Wolfe, B.L., Pollak, S.D.: Association of child poverty, brain development, and academic achievement. JAMA Pediatr. 169(9), 822–829 (2015)
82. Henseler, J., Ringle, C.M., Sinkovics, R.R.: The use of partial least squares path modeling in international marketing New challenges to international marketing. Emerald Group Publishing Limited, Bingley (2009)
83. Fassott, G., Henseler, J., Coelho, P.S.: Testing moderating effects in PLs path models with composite variables In: Industrial Management & Data Systems. Emerald Group Publishing Limited, Bingley (2016)
84. Geisser, S.: The predictive sample reuse method with applications. J. Am. Stat. Assoc. 70(350), 320–328 (1975)
85. Stone, M.: Cross-validatory choice and assessment of statistical predictions. J. Roy. Stat. Soc. Ser. B Methodol. 36(2), 111–133 (1974)
86. Lorenzo-Romero, C., Alarcón-del-Amo, M.-D.-C.: Constantineides, E: Determinants of use of social media tools in retailing sector. J. Theor. Appl. Electron. Commer. Res. 9(1), 44–55 (2014)
87. Shin, D.-H.: User experience in social commerce: in friends we trust. Behav. Inf. Technol. 32(1), 52–67 (2013)
88. Yue, L., Chen, W., Li, X., Zuo, W., Yin, M.: A survey of sentiment analysis in social media. Knowl. Inf. Syst. 60(2), 617–663 (2019)
89. Darko-Adjei, N.: Assessing the impact of social media platforms on students learning activities in the University of Ghana amidst the COVID-19. Library Philosophy and Practice (e-journal). 5216 (2021). https://digitalcommons.unl.edu/libphilprac/5216
90. Mramba, N., Apiola, M., Kolog, E.A., Sutinen, E.: Technology for street traders in Tanzania: a design science research approach. Afr. J. Sci. Technol. Innov. Dev. 8(1), 121–133 (2016)
91. Phua, P.L., Wong, S.L., Abu, R.: Factors influencing the behavioural intention to use the internet as a teaching-learning tool in home economics. Procedia. Soc. Behav. Sci. 59, 180–187 (2012)
92. Abu-Al-Aish, A., Love, S.: Factors influencing students’ acceptance of m-learning: an investigation in higher education. Int. Rev. Res. Open Distrib. Learn. 14(5), 82–107 (2013)
93. Lin, J.W., Lin, H.C.K.: User acceptance in a computer-supported collaborative learning (CSCL) environment with social network awareness (SNA) support. Australas. J. Educ. Technol. 35(1), 3395 (2019)

Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.