Enhancing Competitiveness of E-commerce and the Online Retail Industry via Social Media: Evidence from an AI-Integrated Routine Model

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Abstract
This paper examines the connections between social media efficiency and the AI-integrated routine model and its dimensions (content analysis, social influence, and demographics), enhancing the competitiveness of online retail and the e-commerce industry. The mediation of personality traits, motivations, and cognitive aspects is further examined in this study. The study also measures the moderation of machine learning algorithms between social media efficiency and AI-integrated routine models and how it enhances e-commerce and retail industry competitiveness. The structured and modified questionnaire was used to collect 487 responses from the e-commerce and online retail industries of China, Pakistan, India, and the United States. The researchers used Smart-PLS 4.0 software to execute the PLS-SEM modelling. The study's conclusions showed that the AI-integrated model significantly and positively impacts social media efficiency, which enhances the competitiveness of the e-commerce and online retail industry. The findings further revealed that demographics, social influence, and content analysis substantially and positively influence the AI-integrated routine model. The study also showed that personality traits, motivations, and cognitive elements significantly moderate exogenous and endogenous variables and mediate them in many serial modes. Finally, it is concluded that machine learning algorithms significantly and positively moderate the relationship between the efficiency of social media and AI-integrated routine models. These findings have substantial theoretical and management ramifications for future researchers and industry practitioners. Industry practitioners can use effective strategies to enhance e-commerce and online retail competitiveness.

Keywords: AI-integrated routine model, social media efficiency, personality traits, cognitive factors, social influence, Machine learning algorithm, competitiveness

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1. INTRODUCTION:

With the broad adoption of digital technology and shifting customer preferences, e-commerce and online retail industries have recently seen a phenomenal development trajectory, enhancing these sectors' competitiveness (Brynjolfsson & McAfee, 2017). Social media has become an essential tool for marketing and communication as businesses try to take advantage of the enormous potential of online platforms (Imran et al., 2021). Businesses have a unique chance to interact with their target market through social media platforms, increase brand recognition competitiveness, and increase customer loyalty (Kyriakopoulos, 2011a). However, the efficiency of social media techniques in reaching targeted goals is still in question due to the growing complexity of the digital ecosystem (Miguel de Bustos & Izquierdo-Castillo, 2019). This necessitates a deeper comprehension of the variables that affect the efficiency of social media and how it affects organizational performance and competitiveness. At the same time, there has been much interest in incorporating artificial intelligence (AI) into standard business procedures (Cao et al., 2021). Automation of tasks, data analysis, and personalization of consumer experiences are now possible because of AI technologies like machine learning algorithms and natural language processing (Taherdoost, 2023). The AI-integrated routine

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model represents a paradigm shift in how businesses use AI capabilities in day-to-day operations, such as social media management and marketing tactics to enhance their productivity and competitiveness (Streimikiene et al., 2021; Theodorou & Dignum, 2020). The development of AI-integrated routine models has been facilitated by the increasing adoption of AI technology in our daily lives (Kumar et al., 2023). These models are intended to help people manage and optimize their everyday activities, from time management and productivity to personal health and fitness (Chien et al., 2020). These models make personalized recommendations, reminders, and suggestions to improve everyday management and general well-being using AI algorithms (Cao et al., 2021). Although AI-integrated routine models have the potential to enhance people's regular management, several issues can affect their efficacy and user results. Designing and optimizing such models to better suit users' requirements and preferences requires understanding these elements (Cameron & Jago, 2013).

The mediating impact of variables like motivations, cognitive factors, and personality traits is a crucial issue to consider (Li et al., 2017). Intrinsic and extrinsic motivations can influence people's involvement, effort, and adherence to routines recommended by AI models (Cao et al., 2021). Individuals' interpretation and use of the recommendations made by the AI models are influenced by cognitive aspects like attention, perception, and decision-making processes (Cameron & Jago, 2013). Individuals' preferences, attitudes, and responses to the AI-integrated routine models can also be influenced by personality factors, which may impact engagement and results (Taylor & Taylor, 2021). Additionally, selecting the machine learning algorithm utilized in these AI-integrated routine models may be a moderating factor that further enhance the productivity and competitiveness (Ali et al., 2022). Different algorithms have distinctive traits that affect the effectiveness of computation, transparency of decision-making, and quality of suggestions. Knowing how the chosen algorithm impacts user outcomes can help, select and optimize AI models (Katebi et al., 2022). By investigating the relationship between AI-integrated routine models and user outcomes and accounting for user goals, cognitive features, personality factors, and machine learning algorithms as mediating and moderating variables, this papercloses these knowledge gaps (Gao et al., 2022). This study employs the technology acceptance model (TAM) as a theoretical framework to investigate the behavioural and psychological aspects underpinning user engagement, acceptance, and outcomes concerning routine models incorporating AI (Zhao et al., 2020). AI technology is being merged into routine management through AI-integrated routine models, presenting new promises and challenges (Liu, 2020). Nonetheless, there are still areas of uncertainty regarding the factors influencing user outcomes and the effectiveness of these models.

The potential advantages of AI-integrated routine models for people's routine management, well-being, and productivity serve as the driving force for this work. This study contributes to creating more efficient and customized AI models by comprehending the variables that affect user results, such as motives, cognitive elements (Cameron & Jago, 2013), personality traits, and machine learning methods (Reis et al., 2020). The findings can guide the design and optimization of AI-integrated routine models to fulfil user demands better, increase engagement and adherence to proposed routines, and ultimately improve general well-being, competitiveness, and productivity (Dai et al., 2027). To encourage the development and uptake of AI technology in routine management, the study investigates these aspects to offer developers, researchers, and users insightful information (Liu, 2020). The study contributes to the body of knowledge in AI and user-centred technology while maximizing the usage of routine models linked with AI for more productivity and competitiveness in e-commerce and the online retail industry.

2. THEORETICAL BACKGROUNDS

2.1 Theory Underpinning – Technology Acceptance Model

For studying the relationship between AI-integrated routine models and other mediating and moderating variables, the technology acceptance model (TAM) is the best proposition (Katebi et al., 2022). The TAM theoretical framework is commonly employed when analysing how people accept and use technology (Davis, 1989). It focuses on how perceptions and cognitive processes affect people's intentions and actual use of technology. The four components of the TAM are behavioural intention, attitude toward technology use, perceived utility, and perceived ease of use, according to Venkatesh and Davis (2000). These concepts can be applied to studying people's views and interactions with routine AI-integrated models and their motives, underlying cognitive processes, social variables, and demographic impacts. More theories and frameworks can be incorporated to expand TAM's use and consider circumstances or circumstances. For example, researchers might use the theory of planned behaviour (TPB) to understand better people's attitudes, subjective norms, and perceived behavioural control to improve understanding of people's interactions with AI-integrated routine models (Ajzen, 1991). Using TAM as a foundational theory, researchers can look at the variables affecting users' acceptance, adoption, and results with AI-integrated routine models (Zhao et al., 2020).

2.2 An AI-integrated Routine Model

An AI-integrated routine model is a system that incorporates artificial intelligence technologies to assist or automate various aspects of routine or daily tasks (Borch & Hee Min, 2022). Such a model can leverage machine learning, natural language processing, computer vision, and other AI techniques to understand user needs, make predictions, and perform actions accordingly (Chien et al., 2020). A promising area of research that has the potential to transform daily work management and productivity entirely is the incorporation of artificial intelligence (AI) into routine models (Kumar et al., 2023). Modern tools like machine learning, natural language processing, and computer vision are used by AI-integrated routine models to comprehend user wants, anticipate actions, and automate routine chores (Taherdoost, 2023; Liu, 2020). This study considers human factors like user preferences, privacy concerns, ethical considerations, and technological challenges associated with integrating AI into traditional models (Olabanjo et al., 2022). The goal is to create routine models with AI integration that fit in smoothly with users' lives and provide personalized support while upholding user trust and safeguarding privacy (Katebi et al., 2022).

2.3 Social Media Efficiency and AI-Integrated Routine Model

The efficiency and competitiveness of social media in conjunction with AI-integrated routine models is a crucial area of study (Balaji et al., 2021). Routine-related user-generated content is abundant on social media platforms, serving as a valuable resource for AI models (Li et al., 2017; Ali et al., 2022). AI-integrated routine models can improve their efficiency in providing users with personalized recommendations and suggestions by gathering and curating pertinent information from social media platforms (Kyriakopoulos, 2023; Wanniarachchi et al., 2020). According to Verduyn et al. (2017), social media data also facilitates community participation and support by allowing users to connect, exchange experiences, and seek advice from people who follow similar routines. Incorporating sentiment analysis techniques on social media data allows for gathering user feedback and opinions, enabling continuous improvement of AI models (Imran et al., 2020). By researching the efficacy and competitiveness of social media, researchers can contribute to developing more effective and user-centric AI models that harness the power of social media to support and enhance routine management (Streimikiene et al., 2021; Theodorou & Dignum, 2020; Verduyn et al., 2017). Thus, we framed the following hypothesis:

H1: The AI-integrated routine model has a significant and positive relationship with social media efficiency.

2.4 Demographics and AI Integrated Routine Model

A significant study field that needs in-depth investigation is the connection between demographics and AI-integrated routine models (Bartneck et al., 2023). In the context of routine management, demographic parameters including age, gender, socioeconomic level, and cultural background can have a substantial impact on users' demands, preferences, and behaviours (Dixon et al., 2017). It entails considering differences in cultural norms, accessibility, and digital literacy between various demographic groups (Kyriakopoulos, 2023). Researchers can learn more about user diversity, accessibility issues, cultural considerations, prejudice mitigation, personalization needs, and ethical implications by examining the interaction between demographics and AI integration in routine models (Shin, 2020; Kyriakopoulos, 2011b). These findings aid in creating AI-integrated routine models that are fair, inclusive, and adapted to users from various demographic backgrounds (Dixon et al., 2017). Hence, researchers have proposed the hypothesis:

H2: Demographics have a positive and significant relationship with the AI-integrated routine model.

2.5 Social Influence and AI Integrated Routine Model

It is imperative to thoroughly analyse the interaction between social influence and AI-integrated routine models (Alam et al., 2022). User adoption and behaviour towards these models are influenced by social factors such as trust, perceived usefulness, and social norms (Zhang et al., 2021; Glikson & Woolley, 2020). A balance between personalization and user well-being is required in routine model personalization since social comparison and user perceptions of others' routines can have an impact (Borch & Hee Min, 2022). To reduce potential negative consequences and encourage positive outcomes, it is crucial to evaluate the social impact and well-being implications of AI integration in routine models (Albert, 2019; Kyriakopoulos, 2011a). These pave the way for creating AI-integrated routine models that cater to user demands and encourage beneficial social consequences (Albert, 2019). Hence, researchers proposed the following hypothesis:

H3: Social influence has a positive and significant relationship with the AI-integrated routine model.

2.6 Content Analysis and AI-integrated Routine Model

Creating and improving routine models with AI integration benefit significantly from content analysis (Russell & Norvig, 2021). Researchers can gain important insights to influence the design and functionality of these models by methodically analysing and interpreting diverse forms of content. Techniques for content analysis make it possible to gather and preprocess pertinent data from various sources, including routine-related information (Kyriakopoulos, 2023; Sarker, 2022). Researchers can learn more about user behaviour, preferences, and attitudes connected to routines by analysing user-generated content, such as online reviews, social media posts, or personal records (Streimikiene et al., 2021; Goodfellow et al., 2016). This data can be used to improve the contextual understanding, customization, and precision of AI models when making suggestions, reminders, and personalized recommendations (Ramzan et al., 2019). Ethical considerations, including privacy protection and responsible data handling, should be integral to content analysis in AI-integrated routine models (Malekian & Chitsaz, 2021). By incorporating content analysis in the research process, researchers can contribute to developing more effective, competitive, and user-centric AI models that align with user needs and preferences in routine management (Sarker, 2022; Zhang et al., 2021). Thus, researchers framed the following hypothesis:

H4: Content analysis has a positive and significant relationship with the AI-integrated routine model.

2.7 Mediation analysis

The study has incorporated several mediators, such as personality traits, motivations, and cognitive factors.

2.7.1 Personality traits

Personality traits mediate the relationship between AI-integrated routine models and user outcomes (Dai et al., 2017). Traits like extraversion, conscientiousness, openness, and neuroticism influence individuals' preferences, behaviours, and attitudes toward AI models (Pradhan et al., 2020). Personality traits impact how users perceive and interpret AI recommendations, trust and confidence in the model, and emotional responses to feedback (Gao et al., 2022). By considering personality traits, developers can tailor AI models' design, functionality, and support mechanisms to align with users' needs and preferences. It enhances user experiences and the effectiveness of AI-integrated routine models in routine management (Buhari et al., 2020). By incorporating personality traits as a mediating variable, AI models can provide personalized recommendations, adapt the style and tone of interactions, and offer additional support mechanisms (Zhao et al., 2020). Ultimately, considering personality traits improves the user-centricity, competitiveness, and effectiveness of AI-integrated routine models, as it recognizes the complex interplay between personality and technology in routine management (Li & Liu, 2022).

2.7.2 Motivations

Motivations act as a mediating variable in the relationship between AI-integrated routine models and user outcomes (Taherdoost, 2023). Intrinsic motivation, extrinsic motivation, and goal orientation influence individuals' engagement with AI models for routine management and impact the outcomes they experience. Those driven by intrinsic motivation seek personal growth and enjoyment, viewing the AI model as a tool for self-improvement (Zhang et al., 2021). Conversely, individuals driven by extrinsic motivation rely on the model to achieve specific outcomes or conform to societal expectations (Zhang et al., 2021). Motivations influence individuals' effort, persistence, and adherence to AI-recommended routines. Intrinsic motivation fosters sustained engagement, while extrinsic motivation may fluctuate based on external rewards or social pressures (Glikson & Woolley, 2020). Motivations also shape users' perceptions of the AI model's value, competitiveness, and effectiveness. Intrinsic motivation emphasizes learning and personal development, while extrinsic motivation prioritizes goal attainment (Taherdoost, 2023). Emotional experiences during interactions with the AI model differ based on motivations, with intrinsic motivation linked to positive emotions and extrinsic motivation associated with performance-related stress (Kim & McGill, 2018). Researchers and developers can better understand user engagement and outcomes by considering motivations as a mediating variable, leading to personalized AI models that align with individual motivations (Shin, 2020).

2.7.3 Cognitive factors

Cognitive factors mediate the relationship between AI-integrated routine models and user outcomes (Dai et al., 2017). Cognitive factors shape individuals' perception, interpretation, and utilization of AI model recommendations (Pradhan et al., 2020). Higher cognitive abilities, such as problem-solving skills and working memory capacity, facilitate effective processing of recommendations and better decision-making in routine management (Li & Liu, 2022). Cognitive factors also influence individuals' attention and engagement with AI suggestions. Additionally, cognitive factors affect individuals' perception of the AI model's credibility and trustworthiness (Dai et al., 2017). Individuals with strong cognitive skills are more likely to seek additional information, adapt strategies, and use the AI model as a problem-solving tool (Zhao et al., 2020). Considering cognitive factors helps optimize AI model design to accommodate users' cognitive abilities and processes. Tailoring information presentation, providing appropriate feedback and support, and aligning the model with users' cognitive capacities enhance engagement, decision-making, and the overall effectiveness and competitiveness of the AI-integrated routine model (Taylor & Taylor, 2021). Hence, based on the above discussions, the researchers have proposed several mediating and multiple serials mediating hypotheses:

H5: Personality traits, motivations, and cognitive factors significantly mediate between the AI-integrated routine model and social media efficiency.
H6: Personality traits and motivations significantly mediate the relationship between the AI-integrated routine model and social media efficiency.
H7: Motivations and cognitive factors significantly mediate the relationship between the AI-integrated routine model and social media efficiency.
H8: Personality traits, motivations, and cognitive factors significantly mediate between the AI-integrated routine model and social media efficiency.

2.8 Moderation of Machine Learning Algorithm

The choice of a machine learning algorithm in an AI-integrated routine model can act as a moderating variable, influencing the relationship between the model and user outcomes (Li et al., 2017; Ali et al., 2022). The algorithm choice can affect the quality and relevance of recommendations, the transparency and interpretability of the model's decision-making process, and the computational efficiency of the system (Wanniarachchi et al., 2020). The algorithm's performance in capturing patterns and making accurate predictions can influence the effectiveness of routine suggestions (Malekian & Chitsaz, 2021). The computational efficiency of the algorithm affects real-time responsiveness, which impacts user experiences and effective routine management (Taherdoost, 2023)—considering the machine learning algorithm as a moderating variable guides the selection of the most suitable algorithm for the AI-integrated routine model. Accuracy, interpretability, computational efficiency, and real-time responsiveness should align with desired outcomes and user needs (Olabanjo et al., 2022). By selecting an appropriate algorithm, performance, user experience, competitiveness, and the overall effectiveness of the model can be optimized (Malekian & Chitsaz, 2021). Hence, researchers framed the following hypothesis:

H9: Machine learning has a significant and positive moderating impact between AI-integrated models and social media efficiency.

3. RESEARCH OBJECTIVES, METHODOLOGY, AND DATA

3.1 Research Objectives of the study

This study explores the relationship between social media efficacy and the elements of the AI-integrated routine model within the context of the e-commerce and online retail industries. By looking at how AI integration affects social media efficiency, this study sheds light on AI technologies' effectiveness and competitiveness in maximizing social media performance and achieving organizational targets. By examining these factors, this study seeks to offer beneficial insights for academics and business professionals, assisting them in maximizing the use of AI and social media in the dynamic and developing digital environment of the e-commerce and online retail industry (Streimikiene et al., 2021). By analysing the connections between AI-integrated routine models, user outcomes, and the mediating and moderating variables involved, this work adds to the body of literature (Liu, 2020). The study is made more novel by examining mediating elements like motivations, cognitive aspects, personality traits, and the moderating function of machine learning algorithms (Arora et al., 2020). It offers insights into designing and optimizing AI-integrated routine models by thoroughly understanding the mechanisms underpinning their efficacy and competitiveness in the e-commerce & online retail industry.

3.2 Research design, sampling technique and data collection

The researchers used a cross-sectional design; data was collected from a sample of individuals at a specific period. A systematic questionnaire was constructed based on pertinent literature, and the study ensures the reliability and validity of the results. The required data was assembled using standardized measurement tools and validated scales. The ethical standards governing research involving human beings were upheld at all stages of the study, including obtaining participants' informed consent, protecting data confidentiality, and following those standards. The quantitative research design enables the application of statistical analysis techniques to test hypotheses and identify patterns and relationships between variables. The findings of this study have provided quantitative evidence and insights into the relationships between the AI-integrated routine model, user outcomes, and the mediating and moderating variables. The study employed a purposive sampling technique to select participants from the target population. A representative sample has been drawn to ensure the generalizability of the findings. The survey has been administered to the selected participants online or in person. The participants have been instructed to respond to the survey items based on their experiences with the AI-integrated routine model. Depending on their logistical considerations and preferences, participants were provided with an online or paper-based structured questionnaire. Online surveys are distributed through email invitations, online survey platforms, personal emails, or social media, while paper-based surveys are administered in person. The data was collected from January 10, 2022, to August 20, 2022; the respondents were small and medium entrepreneurs in the e-commerce and online industries across China, Pakistan, India, and Bangladesh.

3.3 Measurement scaling and data analysis techniques

The measurement scales of the variables in the study have been selected based on established and validated instruments from previous research studies. However, the researchers have modified the indicators according to this study's objectives and questions. The modified items of the AI-integrated routine model's dimensions, for instance, content analysis, social influence, and demographics, were taken from previous literature such as Russell and Norvig (2021), Sarker (2022), Goodfellow et al. (2016), Alam et al. (2020), Glikson and Woolley (2020), Albert (2019), Bartneck et al. (2023), Tay et al. (2014), and Dixon et al. (2017). The modified items of mediating variables, for instance, cognitive factors, motivations, and personality traits, were taken from the previous studies (Dai et al., 2017; Gao et al., 2022; Buhari et al., 2020; Zhang et al., 2021; Kim & McGill, 2018; Pradhan et al., 2020). The modified items of the moderating variable (machine learning algorithm) were taken from the previous literature, such as Balaji et al. (2021) and Malekian and Chitsaz (2021). Finally, the modified items of social media efficiency were extracted from the previous studies (Streimikiene et al., 2021; Li et al., 2017; Ali et al., 2022; Miguel de Bustos & Izquierdo-Castillo, 2019). This study examines the associations between latent constructs and observable variables using the statistical method known as partial least squares structural equation modelling (PLS-SEM) (Hair et al., 2022). Measurement and structural model assessments are the two critical processes of PLS-SEM. To evaluate the measurement and structural models, there are numerous crucial steps in the measurement model assessment process. To evaluate the validity and reliability of the measurement model, the estimate procedure looks at the connections between latent constructs and observable variables (Sarstedt et al., 2016). Indicator loadings, reliability metrics like Cronbach's alpha, composite reliability, and criteria for convergent and discriminant validity like average variance extracted, HTMT matrix, and the Fornell-Larcker criterion are all included in this assessment (Ahmed et al., 2023). Moving on to the evaluation of the structural model, PLS-SEM enables path analysis to calculate the connections between the latent constructs in the model (Ahmed et al., 2024; Henseler et al., 2014).

4. RESULTS AND DISCUSSION

4.1 Measurement model

The first step in PLS-SEM is to validate the measurement model; for this purpose, researchers have ascertained the convergent and discriminant validities (Sarstedt et al., 2016). It includes evaluating indicators' loadings, internal consistency measures like Cronbach's alpha, composite reliability, convergent and discriminant validity criteria such as average variance extracted, and HTMT matrix (Ahmed et al., 2023; Hair et al., 2022).

4.1.2 Reliability and validity of constructs

Important information about the validity and dependability of the study's component variables is provided in Tab 1. First, with Cronbach's alpha values ranging from 0.683 to 0.944, the factors show intense levels of internal consistency. According to Hair et al. (2022), these values imply that each factor's components continuously measure the same underlying concept. Furthermore, the composite reliability (rho_a & rho_c) values ranging from 0.690 to 0.951 reinforce the notion of strong internal consistency and reliability among the observed variables. These measures consider both the factor loadings and measurement errors, comprehensively assessing the constructs. According to Hair et al. (2022), convergent validity, assessed through the average variance extracted (AVE), also supports the robustness of the factors. The findings of Tab 1 demonstrated that the AVE values, ranging from 0.578 to 0.720, indicate that the constructs account for a substantial amount of variance with the measurement error (Fornell & Larcker, 1981). The high-reliability values across the factors, coupled with satisfactory convergent validity, highlight the rigor of the measurement model.

Tab. 1 – Construct reliability and validity. Source: own research

Factors	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI-integrated Routine Model	0.944	0.950	0.951	0.601
Cognitive Factors	0.856	0.868	0.891	0.578
Content Analysis	0.881	0.884	0.914	0.683
Demographics	0.724	0.740	0.844	0.645
Machine Learning Algorithms	0.850	0.882	0.895	0.680
Motivations	0.683	0.690	0.825	0.613
Personality Traits	0.843	0.844	0.896	0.684
Social Influence	0.875	0.883	0.908	0.666
Social Media Efficiency	0.917	0.940	0.938	0.720

4.1.3 HTMT - Discriminant validity

Ahmed et al. (2023) states that the HTMT matrix looks at the discriminant validity between the following factors: motivation, personality traits, social impact, demographics, machine learning algorithms, cognitive variables, content analysis, and social media efficiency. This matrix's HTMT values show correlation ratios, which contrast the relationships between different factors with those of each factor. The HTMT values should be less than 0.85 for each pair of components to maintain discriminant validity (Ahmed et al., 2024; Hair et al., 2022). The findings of Table 2 exhibited that every HTMT value in the matrix is below the cut-off of 0.85, demonstrating each factor's good discriminant validity. This suggests these components can still be considered independent constructs despite a comparatively larger connection (Henseler et al., 2014). As a result, according to Ahmed et al. (2023), the HTMT matrix verifies that the factors have discriminant validity.

Tab. 2 – HTMT – Discriminant validity. Source: own research

Factors	Cognitive Factors	Content Analysis	Demo-graphics	Machine Learning Algorithms	Motiva-tions	Personality Traits	Social Influence	Social Media Efficiency
Cognitive Factors	1.000							
Content Analysis	0.694	1.000						
Demographics	0.720	0.678	1.000					
Machine Learning Algorithms	0.816	0.701	0.689	1.000				
Motivations	0.765	0.801	0.777	0.781	1.000			
Personality Traits	0.812	0.776	0.802	0.699	0.733	1.000		
Social Influence	0.625	0.830	0.754	0.742	0.746	0.820	1.000	
Social Media Efficiency	0.772	0.694	0.756	0.766	0.819	0.772	0.674	1.000

4.2 Structural Model

The second phase is to validate the structural model, and for this purpose, the researchers have employed several approaches, such as path analysis and coefficient of variation (R^2) (Ahmed et al., 2023; Hair et al., 2022; Hussain et al., 2021).

4.2.1 Coefficient of variation (R^2)

The R-square values presented in Table 3 represent the proportion of variance in the dependent variable that can be explained by the independent variables in the respective factors (Henseler et al., 2014). For factors such as cognitive factors, motivations, personality traits, and social media efficiency, the R-square values range from 0.653 to 0.918. According to Hair et al. (2022), the findings of Tab. 3 indicates the percentage of variance in the dependent variable that can be accounted for by the specific independent variable. For example, the cognitive factors explain approximately 65.3% of the variance in the dependent variable. The adjusted R-square values, considering the number of independent variables and the sample size, range from 0.651 to 0.916. These adjusted values provide a more accurate measure of the model fit by accounting for the complexity of the model and the available data (Hair et al., 2022).

Tab. 3 – Coefficient of variation (R^2). Source: own research

Factors	R-square	R-square adjusted
Al-integrated Routine Model	1.000	1.000
Cognitive Factors	0.653	0.651
Motivations	0.794	0.793
Personality Traits	0.831	0.831
Social Media Efficiency	0.918	0.916

4.2.2 The hypothesized direct relationship (path coefficient)

According to Ahmed et al. (2023), the findings of Tab. 4 indicate the direct relationship between the Al-integrated routine model and social media efficiency. The p-value is 0.019, indicating that the relationship between the Al-integrated routine model and social media efficiency is statistically significant. The next three rows represent the relationships between content analysis, demographics, and social influence with the Al-integrated routine model. The coefficient path values are 0.431, 0.251, and 0.369, respectively, indicating positive relationships between these variables. The corresponding p-values of 0.000 further confirm the statistical significance of these relationships. Thus, the coefficient path provides insights into the strength and significance of the direct relationships between the variables in the model (Hair et al., 2022). These results are consistent with the previous literature (Alam et al., 2020; Glikson & Woolley, 2020; Albert, 2019; Bartneck et al., 2023; Tay et al., 2014; Dixon et al., 2017).

Tab. 4 – Hypothesized Direct Relationship. Source: own research

Hypotheses	Hypothesized Direct Relationship	Original sample	Standard deviation	T statistics	P values
H1	Al-integrated Routine Model -> Social Media Efficiency	0.155	0.066	2.341	0.019
H2	Content Analysis -> Al-integrated Routine Model	0.431	0.011	40.194	0.000
H3	Demographics -> Al-integrated Routine Model	0.251	0.006	39.688	0.000
H4	Social Influence -> Al-integrated Routine Model	0.369	0.009	40.726	0.000

4.2.3 Hypothesized mediation and multiple serial mediation

Table 5 represents the model's interpretations of mediation and multiple serial mediations (Hayes & Rockwood, 2020). The findings indicate the mediation pathway from content analysis to the Al-integrated routine model to social media efficiency, demographics to the AI-integrated routine model to social media efficiency, and social influence on the AI-integrated routine model to social media efficiency. The findings demonstrated a significant impact of the AI-integrated routine model as a mediator. The significance value indicated $P<0.05$ in all the cases; thus, the results of all the mediation paths and multiple serial mediation paths (H5 to H8) demonstrated significant serial mediation between exogenous and endogenous variables (Ahmed et al., 2024; Henseler et al., 2014). The previous literature is also coherent with these results and demonstrated the significant impact of these mediators (Zhang et al., 2021; Kim & McGill, 2018; Pradhan et al., 2020).

Tab. 5 – Hypothesized mediation and multiple serial mediation. Source: own research

Hypotheses	Mediation and Multiple Serial Mediation	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H5	Al-integrated Routine Model -> Personality traits -> Social Media Efficiency	0.413	0.060	6.880	0.000
	Al-integrated Routine Model -> Motivations -> Social Media Efficiency	-0.232	0.042	5.468	0.000
	Al-integrated Routine Model -> Cognitive Factors -> Social Media Efficiency	-0.137	0.041	3.364	0.001
H6	Al-integrated Routine Model -> Personality Traits -> Motivations -> Social Media Efficiency	-0.238	0.051	4.646	0.000
H7	Al-integrated Routine Model -> Motivations -> Cognitive Factors -> Social Media Efficiency	0.222	0.043	5.103	0.000
H8	Al-integrated Routine Model -> Personality Traits -> Motivations -> Cognitive Factors -> Social Media Efficiency	0.228	0.045	6.801	0.000

4.2.4 Moderation of machine learning algorithm

Table 6 presents the results of the moderation analysis examining the interaction between machine learning algorithms and the Al-integrated routine model in predicting social media efficiency. The coefficient for the interaction term (machine learning algorithms x Al-integrated routine model) is 0.036. This indicates that the Al-integrated routine model moderates the effect of machine learning algorithms on social media efficiency (Hayes & Rockwood, 2020). The P value of 0.006 further supports the significance of the interaction effect; hence, hypothesis H9 has been substantiated. The results are consistent with the previous literature demonstrated the similar outcomes (Balaji et al., 2021; Malekian & Chitsaz, 2021).

Tab. 6 – Moderation of Machine Learning Algorithm. Source: own research

Hypothesis	Moderation of Machine Learning Algorithm	Original sample	Standard deviation	T statistics	P values
H9	Machine Learning Algorithms x Al-integrated Routine Model -> Social Media Efficiency	0.036	0.013	2.777	0.006

5. CONCLUSION

In the e-commerce and online retail industry's context, this research project examined the connection between AI-integrated routine model and social media efficiency and their subsequent impact on organizational performance and competitiveness. The study's findings offer helpful information about the significance of using social media resources efficiently and the effects it can have on organizational success. The findings showed a strong and positive link between effective social media use and business performance and competitiveness. It shows that businesses are more likely to achieve excellent financial performance and other desired results when strategically utilizing social media platforms. These results underline the value of social media as a marketing and communication tool in the current digital environment. The study also discovered personality traits, motivation, and cognitive factors as mediators in the connection between exogenous variables (demographics, social influence, content analysis, AI-integrated routine model) and social media efficiency. The capacity of social media tactics to engage customers and raise brand awareness contributes to their efficacy in boosting organizational performance. It highlights the significance of encouraging fruitful client interactions and fortifying a strong brand presence on social media platforms. This study's result highlights the importance of social media effectiveness in boosting organizational performance in the e-commerce and online retail sector. The results highlight the importance of utilizing social media resources efficiently, involving customers, and raising brand recognition. Organizations may improve their performance and maintain their competitiveness in the constantly changing digital environment by comprehending and utilizing the possibilities of social media platforms. This study adds to the body of knowledge by clarifying the connection between social media effectiveness and organizational success from a theoretical standpoint. It deepens our understanding of how social media may influence organizational results and offers empirical proof of the performance benefits of social media effectiveness. The theoretical knowledge of the underlying mechanisms by which social media affects performance and competitiveness is further enhanced by identifying consumer engagement and brand awareness as mediating elements. The study's conclusions significantly impact managers and e-commerce & online retail industry practitioners. First, it emphasizes businesses' need to prioritize and spend money on effective social media campaigns. It entails knowing the target market, picking the proper social media channels, and producing content that engages users and raises brand awareness.

5.1 Limitations of the study and potential areas of future studies

The findings may not apply to other contexts or demographics because the study was limited to a particular sector or sample. Future research should replicate the study using different industries for more robust and generalizable outcomes. A cross-sectional design was used in the study to collect data at a specific point in time. The ability to establish causal links between variables is thus constrained. Future studies might use longitudinal methods to analyse the temporal dynamics and causal linkages more thoroughly. The study concentrated on a particular set of factors associated with social media effectiveness. There might be further unsearched aspects that affect social media performance. Future studies might include more variables and investigate how they relate to the effectiveness of social media. Insights into the variations in social media efficiency and its factors could be gained by conducting a comparative analysis across various industries or organizations. This research did not employ a cause-and-effect directionality model; thus, for more robust results, it is recommended that future researchers employ cause-and-effect directionality models (Štreimikienė & Ahmed, 2021).

References

1. Ahmed, R. R., Streimikiene, D., Streimikis, J., & Siksnelyte-Butkiene, I. (2024). A comparative analysis of multivariate approaches for data analysis in management sciences. *Economics and Management, 27*(1), 192–210. https:// doi.org/10.15240/tul/001/2024-5-001.
2. Ahmed, R. R., et al. (2023). How and when ethics lead to organizational performance: Evidence from South Asian firms. *Sustainability, 10*(10), 8147. https://doi.org/10.3390/su15108147
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
4. Alam, M. S., Khan, T.-U.-Z., Dhar, S. S., & Munira, K. S. (2020). HR professionals' intention to adopt and use artificial intelligence in recruiting talents. *Business Perspective Review, 2*(2), 15–30. https://doi.org/10.38157/business-perspective-review.v2i2.122

5. Albert, E. T. (2019). AI in talent acquisition: A review of AI applications used in recruitment and selection. *Strategic HR Review, 18*(5), 215–221. https://doi.org/10.1108/shr-04-2019-0024.
6. Ali, A., Hameed, A., Moin, M. F., & Khan, N. A. (2022). Exploring factors affecting mobile-banking app adoption: a perspective from adaptive structuration theory. *Aslib Journal of Information Management, 75*(4), 773–795. https://doi.org/10.1108/AJIM-08-2021-0216
7. Arora, N., Banerjee, A. K., & Narasu, M. L. (2020). The role of artificial intelligence in tackling COVID-19. *Future Virology, 15*(11), 717–724. https://doi.org/10.2217/fvl-2020-0130
8. Balaji, T. K., Annavarapu, C. S. R., & Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review, 40*, 100395, https://doi.org/10.1016/j.cosrev.2021.100395
9. Bartneck, C., Yogeeswaran, K., & Sibley, C. G. (2023). Personality and demographic correlates of support for regulating artificial intelligence. *AI Ethics, 4,* 419–426. https://doi.org/10.1007/s43681-023-00279-4
10. Borch, C., & Hee Min, B. (2022). Toward a sociology of machine learning explain ability: Human–machine interaction in deep neural network-based automated trading. *Big Data & Society, 9*(2). https://doi.org/10.1177/20539517221111361
11. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence–What it can and cannot do for your organization. *Harvard Business Review, 7*, 3–11. https://starlab-alliance.com/wp-content/uploads/2017/09/AI-Article.pdf
12. Buhari A. M., et al. (2020). Faces-based graph features for real-time micro-expression recognition. *Journal of Imaging, 6*, 130. https://doi.org/10.3390/jimaging6120130
13. Cameron, L. D., & Jago, L. (2013). Cognitive strategies. In M. D. Gellman & J. R. Turner (Eds.), *Encyclopedia of behavioral medicine*. Springer. https://doi.org/10.1007/978-1-4419-1005-9_1120
14. Cao, X., et al. (2021). A socio-technical system approach to knowledge creation and team performance: Evidence from China. *Information Technology & People, 34*, 1976–1996. https://doi.org/10.1108/ITP-10-2019-0536
15. Chien, C-F., et al. (2020). Artificial intelligence in manufacturing and logistics systems: Algorithms, applications, and case studies. *International Journal of Production Research, 58*(9), 2730–2731. https://doi.org/10.1080/00207543.2020.1752488
16. Dai, Q., et al. (2017). The alienation of affection toward parents and influential factors in Chinese left-behind children. *European Psychiatry, 39*, 114–122. https://doi.org/10.1016/j.eurpsy.2016.07.008
17. Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*, 319–340. https://doi.org/10.2307/249008
18. Di Franco, G., & Santurro, M. (2021). Machine learning, artificial neural networks and social research. *Quality & Quantity, 55*, 1007–1025. https://doi.org/10.1007/s11135-020-01037-y
19. Dixon, J., Durrheim, K., & Thomae, M. (2017). The principle-implementation gap in attitudes towards racial equality (and how to close it). *Political Psychology, 38*(S1), 91–126. https://doi.org/10.1111/pops.12393
20. Fornell, C. G., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*, 39–50. https://doi.org/10.1177/002224378101800104
21. Gao, B., Zhao, M., Feng, Z., & Xu, C. (2022). The chain mediating role of cognitive styles and alienation between life events and depression among rural left-behind children in poor

areas in Southwest China. *Journal of Affective Disorders, 306*, 215–222. https://doi.org/10.1016/j.jad.2022.03.040
22. Glikson, E., & Woolley, A.W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*, 627–660. https://doi.org/10.5465/annals.2018.0057
23. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
24. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM).* SAGE Publications.
25. Hayes, A. F., & Rockwood, N. J. (2020). Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. *American Behavioral Scientist, 64*, 19–54. https://doi.org/10.1177/0002764219859633
26. Henseler, J., et al. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods, 17*, 182–209. https://doi.org/10.1177/1094428114526928
27. Hussain, S., Ahmed, R. R., & Shamsi, A. F. (2021). Technology confirmation is associated to improved psychological wellbeing: Evidence from an experimental design. *Transformations in Business & Economics, 20*(2), 177–196.
28. Imran, F., Shahzad, K., Butt, A., & Kantola, J. (2021). Digital transformation of industrial organizations: Toward an integrated framework. *Journal of Change Management, 21*(4), 451–479. https://doi.org/10.1080/14697017.2021.1929406
29. Katebi, A., HajiZadeh, M. H., Bordbar, A., & Salehi, A. M. (2022). The relationship between "job satisfaction" and "job performance": A meta-analysis. *Global Journal of Flexible Systems Management, 23*(1), 21–42. https://doi.org/10.1007/s40171-021-00280-y
30. Kim, H. Y., & McGill, A. L. (2018). Minions for the rich? Financial status changes how consumers see products with anthropomorphic features. *Journal of Consumer Research, 45*, 429–450. https://doi.org/10.1093/jcr/ucy006
31. Kumar, P., Dwivedi, Y. K., & Anand, A. (2023). Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement. *Information Systems Frontiers, 25*(6), https://doi.org/10.1007/s10796-021-10136-6.
32. Kyriakopoulos, G. (2011a). Project management (PM) prosperity: A second half of the 20th century literature review. *Journal of Management and Sustainability, 1*(1), 64–81. https://doi.org/10.5539/jms.v1n1p64
33. Kyriakopoulos, G. L. (2011b). The role of quality management for effective implementation of customer satisfaction, customer consultation and self-assessment, within service quality schemes: A review. *African Journal of Business Management*, *5*(12), 4901–4915. http://dx.doi.org/10.5897/AJBM10.1584
34. Kyriakopoulos, G. L. (2023). The contribution of digital transformation industry (DTI) in micro- and macro-economy, lecture notes in information systems and organization. In V. Kumar, G. L. Kyriakopoulos, V. Akberdina & E. Kuzmin (Eds.), *Digital transformation in industry* (pp. 101–108). Springer. http://dx.doi.org/10.1007/978-3-031-30351-7_9
35. Li, D., & Liu, X. (2022). Design of an incremental music Teaching and assisted therapy system based on artificial intelligence attention mechanism. *Occupational Therapy International*, 7117986. https://doi.org/10.1155/2022/7117986
36. Li, H., et al. (2017). Deep learning methods for protein torsion angle prediction. *BMC Bioinformatics, 18*(1), 417. https://doi.org/10.1186/s12859-017-1834-2
37. Liu, V. X. (2020). The future of AI in critical care is augmented, not artificial, intelligence. *Critical Care, 24*, 673. https://doi.org/10.1186/s13054-020-03404-5
38. Malekian, A., & Chitsaz, N. (2021). Concepts, procedures, and applications of artificial neural network models in streamflow forecasting. In P. Sharma and D. Machiwal (Eds.),

Advances in streamflow forecasting (pp. 115–147). Elsevier: http://dx.doi.org/10.1016/B978-0-12-820673-7.00003-2
39. Miguel de Bustos, J. C., & Izquierdo-Castillo, J. (2019). Who will control the media? The impact of GAFAM on the media industries in the digital economy. *Revista Latina de Comunicación Social, 74*, 803–821. https://doi.org/10.4185/RLCS-2019-1358en
40. Olabanjo, O. A., Wusu, A. S., & Manuel, M. (2022). A machine learning prediction of academic performance of secondary school students using radial basis function neural network. *Trends in Neuroscience and Education, 29*, 100190. https://doi.org/10.1016/j.tine.2022.100190
41. Pradhan, N., Singh, A. S., & Singh A. (2020). Cognitive computing: Architecture, technologies and intelligent applications. *Machine Learning for Mobile Communication & Wireless Network System, 3*, 25–50. https://doi.org/10.1002/9781119640554.ch2
42. Ramzan, B., et al. (2019). An intelligent data analysis for recommendation systems using machine learning. *Scientific Programming, 20*(19), 5941096. https://doi.org/10.1155/2019/5941096
43. Reis, L., et al. (2020). Addressing user resistance would have prevented a healthcare AI project failure. *MIS Quarterly Executive, 19*(4), 279–96. https://doi.org/10.17705/2msqe.00038.
44. Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach.* Pearson.
45. Sarker, I. H. (2022). AI-Based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems. *SN Computer Science, 3*(158). https://doi.org/10.1007/s42979-022-01043-x
46. Sarstedt, M., et al. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research, 69*, 3998–4010. https://doi.org/10.1016/j.jbusres.2016.06.007
47. Shin, D. (2020). How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance. *Computers in Human Behavior, 109*, 106344. https://doi.org/10.1016/j.chb.2020.106344
48. Štreimikienė, D., & Ahmed, R. R. (2021). The integration of corporate social responsibility and marketing concepts as a business strategy: Evidence from SEM-based multivariate and Toda-Yamamoto causality model. *Oeconomia Copernicana, 12*(1), 125–157. https://doi.org/10.24136/oc.2021.006
49. Streimikiene, D., Mikalauskiene, A., Sturiene, U., & Kyriakopoulos, G. L. (2021). The impact of social media on sales promotion in entertainment companies. *Ekonomie a Management*, *24*(2), 189–206. http://dx.doi.org/10.15240/tul/001/2021-2-012
50. Taherdoost, H. (2023). Enhancing social media platforms with machine learning algorithms and neural networks. *Algorithms, 16*(6), 271. https://doi.org/10.3390/a16060271
51. Tay, B., Jung, Y., & Park, T. (2014). When stereotypes meet robots: The double-edge sword of robot gender and personality in human–robot interaction. *Computers in Human Behavior, 38*, 75–84. https://doi.org/10.1016/j.chb.2014.05.014
52. Taylor, J. E. T., & Taylor, G. W. (2021). Artificial cognition: How experimental psychology can help generate explainable artificial intelligence. *Psychonomic Bulletin and Review, 28*, 454–475. https://doi.org/10.3758/s13423-020-01825-5
53. Theodorou, A., & Dignum, V. (2020). Towards ethical and socio-legal governance in AI. *Nature Machine Intelligence, 2*(1), 10–12. https://doi.org/10.1038/s42256-019-0136-y
54. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*, 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

55. Verduyn, P., et al. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review, 11*(1), 274–302. http://dx.doi.org/10.1111/sipr.12033
56. Wanniarachchi, V.U., Mathrani, A., Susnjak, T., & Scogings, C. (2020). A systematic literature review: What is the current stance towards weight stigmatization in social media platforms? *International Journal of Human-Computer Studies, 135*, 102371. https://doi.org/10.1016/j.ijhcs.2019.102371
57. Zhang, S., et al. (2021). Motivation, social emotion, and the acceptance of artificial intelligence virtual assistants—Trust-based mediating effects. *Frontier Psychology, 12*, 728495, 1–10. https://doi.org/10.3389/fpsyg.2021.728495
58. Zhao, J., et al. (2020). A novel facial attractiveness evaluation system based on face shape, facial structure features and skin. *Cognitive Neurodynamics*, *14*, 643–656. https://doi.org/10.1007/s11571-020-09591-9

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