Bridging Realities into Organizations through Innovation and Productivity: Exploring the Intersection of Artificial Intelligence, Internet of Things, and Big Data Analytics in the Metaverse Environment Using a Multi-Method Approach

Abstract

This study investigates how organizations may increase innovation and productivity through the Metaverse environment efficacy (MVEE), Artificial intelligence usage (AIU), Internet of Things usage (IoTU), and Big Data Analytics usage (BDAU). The study gathers responses from the gaming, information technology, and entertainment industries, using a multi-method involving Partial Least Squares Structural Equation Modeling, Fuzzy-set Qualitative Comparative Analysis, and Artificial Neural Networks to investigate how these technologies might be used to improve the linking of disparate realities in a business context. The use of AI in personalized and decision-support applications, IoT for real-time data collecting, and BDAU for an insights-driven strategy all combine to create a dynamic MVEE ecosystem. The research also delves into theoretical implications concerning the viability of using the MVEE to boost innovation and productivity. This research identifies the applications of using AI, IoT, and BDA to drive organizational performance in terms of innovation and productivity. Also, the research lays out the role of AI, IoT, and BDA in creating a dynamic metaverse ecosystem.

Keywords: Metaverse; Task-Technology Fit theory; Artificial Intelligence; Internet of Things; Big Data Analytics; Integration.

1. Introduction

Technologists, academics, and the general public are all captivated by the still-developing notion of the Metaverse (MV) because of its potential to revolutionize how we communicate and interact in virtual worlds [1]. Joshua [2] defines MV as "a virtual reality (VR) space that utilizes the internet and augmented reality (AR) via avatars and software agents". Kar and Varsha [3] define MV as "a socio-economic immersive cyber-physical ecosystem which is enabled by digital platforms where the interactions are virtually undertaken, and the ecosystem is shaped by the shared values, norms, and goals of the users. These users display a virtual personality in the metaverse (through avatars) and join the platform to seek a common goal of shared value creation, extraction, and exchange through the community of users onboarded in the platform". The MV offers a cohesive platform that enables individuals in various geographical locations to collaborate in real-time and collective work [4]. Consequently, innovation can foster a conducive environment, leading to heightened productivity through the facilitation of more efficient task completion [5]. Efficient MVE affects decision-making within a firm and facilitates the cultivation of an enhanced educational setting, thus enabling the investigation of novel ideas and concepts [6]. For instance, in the realm of VR, the United States military recognizes that the acquisition of new vocational skills, such as equipment repair for trucks or helicopters, entails a significant decision of temporal investment in familiarizing individuals with the spatial arrangement of various components on the machinery [1]. VR technologies are already being embraced and employed by numerous industries to quicken the pace of skill development [2]. Therefore, MVEE plays an important role in business decisions to achieve both innovation in organizations (IO) and productivity in organizations (PO).

Further, artificial intelligence (AI) possesses the capability to examine and assess user behavior, preferences, and interactions, thereby enabling the creation of tailored experiences within MVE [7]. The personalization process guarantees that the virtual environment and the tools provided are tailored to each user's specific tasks and objectives [8]. AI usage (AIU) can propose pertinent content, virtual environments, or social engagements by leveraging users' past data [9]. Moreover, IoT usage (IoTU) is engaged in commercial activities involving cameras, sensors, and technological devices organized in clusters for an extended period [10]. Geolocation tags possess the capability to discern bodily motion, eye fixation, and various physiological processes that are pivotal in emulating a nearly authentic persona while also facilitating the creation of an immersive encounter that closely resembles reality [11]. Now that the MVEE can more easily link to the actual world, the IoT will profoundly affect it. IoTU helps to translate data from the actual world to the virtual world in real-time [12]. In this way, IoTU enables the efficiency of MVE by addressing its issues. To effectively leverage the substantial volume of data and information circulating within the emerging digital economy of efficient MVE, it will be imperative for all parties involved to employ robust analytics solutions [13]. Furthermore, BDA usage (BDAU) is crucial in making decisions for navigating the future digital economy, as the envisioned MVE would significantly expand

[1] https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/innovative-and-practical-applications-of-the-MV (Accessed on 17/07/2023)
[2] https://datatechvibe.com/data/can-working-via-MV-increase-productivity/ (Accessed on 17/07/2023)

the amount and diversity of data in circulation [13], with BDAU enhancing the efficiency of the working environment of MV.

In this way, AIU, IoTU, and BDAU fulfill different necessary tasks to improve the efficiency of MVE. Still, to the best of the authors' knowledge, no previous research investigates the relationships among AIU, IoTU, BDAU, and MVEE for improving IO and PO. Therefore, given the different required tasks completed by AIU, IoTU, BDAU, and efficient MVE, the present research is conducted from the task-technology fit (TTF) perspective. To better understand how technology is used, Goodhue and Thompson [14] develop the TTF, which centers on how well a given piece of technology meets the needs of its intended end users. The TTF theory aims "to add to the body of knowledge on technology utilization in the private and public contexts, which had a limited explanation of how the acceptance of technology contributes to individuals' performance". Therefore, the present research is well-suited to looking from the theoretical lens of TTF. Also, previous research does not extensively explore how these technologies include MVEE to facilitate innovation inside firms and enhance overall productivity. Previous scholars have examined these technologies both individually and in conjunction with one another within the context of the MV; this indicates the importance of these technologies in MVE, as presented in Table 1 of Section 2.1. Further, the TTF model is ideal for identifying the alignment between technology and related tasks, a challenge highlighted by several information systems (IS) studies [15, 16]. The main goal of this study concentrates on the association of digital technologies with MVEE, advancing to innovation and productivity of the firm to measure the alignment of technology and task fit. Although the TTF model has been used to explore the applications of immersive technologies, such as AR and VR [17], limited research has comprehensively addressed the association of digital technologies with MVEE and further to innovation and productivity of the firm. Hence, our study aims to explore this aspect and provide the needed information to understand better. The present study focuses on the intersection of AIU, BDAU, and IoTU for MVEE to bridge realities in companies through innovation and productivity.

This distinctive viewpoint strives to establish a connection between the digital and physical realms, with a particular focus on fostering innovation as well as productivity inside organizations. Through an investigation of the incorporation of these smart technologies within the MVE, this research adds to the comprehension of how these technologies might be used to facilitate tangible commercial results, promoting the development of novel ideas and boosting efficiency. This study offers valuable insights into the potential advantages of incorporating AIU, BDAU, and IoTU for MVEE. Such findings can make a significant contribution to both academic research and industrial practices, as companies seek to harness these technologies to gain a competitive edge and enhance organizational performance.

The present research proposes various hypotheses for the association of AIU, BDAU, and IoTU with MVEE, and additionally, the association of MVEE with IO and PO. Finally, the study offers a hypothesized model to explore the relationships among AIU, BDAU, and IoTU for MVEE to deliver IO and PO. The novelty of the study stems from its holistic examination of the potential synergy between MVEE and digital technologies, such as AIU, IoTU, and BDAU, to enhance innovation and productivity within organizations. The study not only identifies the applications of AI, IoT, and BDA in driving organizational performance, but it also lays out their role in creating an efficient MVE. Further, by exploring the theoretical implications of efficient MVE to increase innovation and productivity, the study extends our understanding of the transformative potential of augmented reality in business contexts. As such, the study opens new opportunities for scholars to investigate and understand how AIU, IoTU, and BDAU are expected to define the future of MVEE and how organizations can use them to be successful in the digital age. In addition, the research deploys partial least squares structural equation modeling (PLS-SEM), fuzzy-set qualitative comparative analysis (fsQCA), and artificial neural network (ANN) analysis to validate the model and hypotheses. The presentation of the paper is as follows. Section 2 focuses on theoretical underpinning and hypothesis development followed by Section 3 where the research methodology is discussed. Section 4 focuses on the results analysis followed by Section 5, which offers a brief discussion of findings followed by various implications, limitations, and future research directions in Section 6. Section 7 is focused on the conclusions of the study.

2. Theoretical background and research hypotheses

2.1. Task-technology fit theory

Task-technology fit (TTF) is a comprehensive theory within the field of information systems. It asserts that the effectiveness of information technology in enhancing performance is contingent upon the alignment between features of the information system and the tasks that organizations carry out [14]. TTF is described as how well human needs and technological capabilities match [18]. It defines if the requirements of the users are completely satisfied by the features of interactive collaborative offices. The services provided by technology are referred to as its features or characteristics [19]. The notion of the fit across a task and technology pertains to the degree of efficiency and effectiveness with which a certain work may be executed using a specific technology [20]. Various terms are used to describe the concept of fit, including "deviation, mediation, moderation, gestalts, covariation, and matching" [21]. Rai and Selnes [22] state that the definition of a task environment in TTF lacks clarity. In particular, the TTF metric fails to include the potential interconnections and interdependencies that may exist across various jobs. The alignment between a given task and its corresponding technology is influenced by the presence of additional interconnected activities that may also use the same technology. Consequently, the concept of TTF is redefined by Rai and Selnes [22] as the degree to which a technology is effectively incorporated into a network of interconnected activities and practices inside a social environment. Although organizational tasks often exhibit interdependencies, research suggests that it remains feasible to assess the compatibility of technology with a specific goal. TTF has been applied as an example framework to explain the proper adoption of information technology in various digital transformation cases. They include ICTs for developing and maintaining online learning content so that it is used in the long run [23] or IoT network systems for disaster management [24] and virtual reality for higher-education learning outcomes or the usage of a decision support system for appropriate decision-making [25]. The TTF model has been tested in some previous empirical studies in the field of hospitality management and reveals the linkages between tasks, technology, usage, user satisfaction, and performance outcomes [26]. It has been used in the cases in hotel settings to describe the usage and adoption of technology among both guests and employees. For example, the study by Lee et al. [27] found that travelers who are likely to shop for tourism are likely to use mobile commerce if the situational context fits the task-technology usage. In addition, Vatanasakdakul et al. [28] claim that while people are more likely to use technology that fits their culture, the effect of the technological fit on the firm's perceived performance is greater than the role of the culture. Fit is about the degree to which technology's features fit the role's demands and vice versa. From the research carried out by Goodhue and Thompson [14] in 1995, it has been the case that research on TTF has consistently maintained that a task and the appropriateness of the technology involved share a direct relationship. This conclusion here should not, however, be mistaken as that the technology is a singular one; in this narrative, we hold our definition of fit as the amalgamation of different technologies and the user's experience. Thus, we can argue that TTF suggests that the technology used in MEE is legit only if digital technologies have advantages in productivity, creativity, and adherence to role demands.

The current research aims to assess the alignment between tasks assigned to stakeholders of efficient MVE and the facilitation of emerging technology adoption. This will be achieved by examining the tasks assigned to stakeholders and the potential of emerging technologies. TTF theory is used to provide theoretical perspectives on the association of adopting cutting-edge digital technologies with the MVEE, resulting in enhanced PO and IO.

After conducting a comprehensive review of existing research, the authors have compiled a summary of pertinent earlier studies in Table 1. This provides an overview of how previous academics explore AIU, BDAU, and IoTU, as well as their interactions with MVEE and subsequent association with business performance.

Table 1: Past studies on the role of various digital technologies in the MV environment (MVE)

S. No.	Author (s)	Usage of digital technology in the MVEE context	Major findings
1.	Tacchino et al. [29]	AI and BDA	They suggest using digital twin technology to improve cognitive phenotyping for people with multiple sclerosis, a chronic neurological disease.
2.	Guo et al. [30]	AI and IoT	This article aims to shed light on how urban libraries in the United States use MV-related technology.
3.	Mozumder et al. [31]	AI and IoT	They demonstrate how the MV may be used to improve the standard of care provided to patients and lengthen their lives by facilitating more assured procedures like the treatment of chronic diseases, physical fitness, and emotional well-being.
4.	Huynh-The et al. [32]	AI, IoT, and Big Data	They cover a wide range of technical topics, including data capture, storage, sharing, interoperability, and privacy, about blockchain-based MV approaches.

5.	Zheng and Yuan [33]	AI and IoT	They provide the most recent findings from studies conducted on the quality of experience in the modern MV.
6.	Teng et al. [34]	AI	They conceptualize avatar-mediated communication by using user-avatar identification, avatar-avatar identification, and social presence.
7.	Lejealle and Dolansky [35]	AI	They discussed users' motivations to engage in this metaverse, through the lens of Self Determination Theory.
8.	Marabelli and Newell [36]	AI and IoT	The metaverse was examined through a sociotechnical perspective, leading to the identification of strategic implications, as well as opportunities and difficulties related to diversity, equity, and inclusion.
9.	Pamucar et al. [37]	AI and IoT	They integrated metaverse with sharing economy transportation applications to achieve sustainability.
10.	Dolata and Schwabe [38]	AI	They applied social construction of technology theory to describe the metaverse as a matter of controversy and state that "the nature and future of the Metaverse is underdetermined and contingent on the ongoing, collaborative processes of sensemaking"

2.2. AI usage and Metaverse environment efficacy

The MV is a major topic of interest in the realm of industrial breakthroughs, mostly driven by the rapid advancement of AI technologies that facilitate the development and functioning of these interconnected digital ecosystems [39]. Also, recent progress in AI contributes to the identification of solutions to address the dangers and issues associated with the emergence of the MV by utilizing BDA [39]. Some examples help illustrate the usefulness of AI in MVEE. In Nike Land on Roblox ("MV-oriented game webpage"), users may interact with virtual sports equipment, play minigames, and build their games [40]. Sales are also generated via the use of non-fungible tokens known as Crypto Kicks in the sale of Nike items in Nike Land [41]. So, AIU in MVE enhances the enjoyment, participation, and loyalty of consumers throughout the purchasing process [42]. Companies in the music and fashion industries were among the first to employ AI to reinvent their brands in the MVE to capitalize on the expanding market for virtual goods [43]. AIU combines and enhances the retail and shopper experience in the MVE so that businesses may better understand their customers' wants and needs [44]. In this way, AIU is compatible with MVE and is effectively incorporated to enhance the MVEE to complete organizational tasks. Thus, the study can hypothesize that:

H1: AIU has a positive association with MVEE.

2.3. IoT usage and Metaverse environment efficacy

Interoperability is a fundamental need for all connected subworlds for MVEE. Nevertheless, it is important to acknowledge that during the early stages of the MVEE, it is not reasonable to assume that the owners of physical assets have already been included in the MVEE [45]. Furthermore, there is no assurance that their services have undergone a complete transformation to facilitate interoperability. Hence, it is essential to consider the association of external resources, such as utilizing IoT devices, to enable the acquisition of information about the physical attributes of objects, particularly when the owners of these assets are not present inside the MVE [45]. In addition, the IoT may be used for MVEE [46], transforming real-time IoT data from the physical world into digital reality in the virtual world to provide wireless and seamlessly linked immersive digital experiences. The IoT may complement the experience interface of consumers in the virtual world formed by AR/VR [47]. To instrument the user's status, such as the health conditions that can provoke a reaction in the virtual environment, medical IoT devices can be mounted to the user's body or a sensor-laden body suit [48]. By tracking the user's body movements, IoT devices may also enhance the virtual fitting room experience in e-commerce. Photos shot with the user's smartphone or weight measured with a smart scale are two examples of how the user's body data can be kept up to date [49]. This removes the experiential boundaries of conventional online buying by letting MVEE customers immerse themselves in a digital copy of the store [49]. The emerging Tactile Internet, which creates a network or network of networks for remote access and control of real or virtual items in real-time by people or machines, may also make use of data collected by the Internet of Things [50]. The integration of IoTU in this manner makes MVE more efficient, which in turn helps an organization to accomplish its goals. Therefore, the research can hypothesize that:

H2: IoTU has a positive association with MVEE.

2.4. BDA usage and Metaverse environment efficacy

Big Data Analytics (BDA) has emerged as a prominent disruptive technology that enables the extraction of valuable insights from vast amounts of data. The use of BDA in the context of MVE can significantly influence the many stakeholders involved [51]. BDAU is responsible for analyzing large volumes of data created inside the MVE to facilitate the development of personalized user experiences [52]. Ensuring user involvement and satisfaction in the MVE is of paramount importance. The BDAU framework offers significant insights into user patterns and expectations, enabling organizations to make informed decisions in developing and optimizing their services and products [53]. This approach facilitates the expansion of organizations, enables prompt adaptation to dynamic market conditions, and delivers tailored experiences to stakeholders in the MVE. BDAU is responsible for the collection and analysis of data provided by users. This process involves identifying popular content, trends, and user preferences. The insights gained from BDAU assist developers in building products that align with these findings, ultimately leading to increased customer satisfaction. BDAU also assumes a significant role in the realm of security management and fraud detection via the examination of extensive datasets [54]. The incorporation of BDAU in this manner enhances the efficiency of MVE, hence facilitating the achievement of the organization's objectives. Therefore, the study can hypothesize that:

H3: BDAU has a positive association with MVEE.

2.5. Metaverse environment efficacy and productivity of the organization

The efficient MVE is a technological solution that facilitates virtual interactions among businesses, improving their collaborative efforts and communication strategies, and leading to better PO [55]. Corporations can assemble teams from various geographical areas, convene in virtual meeting spaces, foster the generation of ideas, and facilitate well-informed decision-making. MVE improves the accessibility and flexibility of organizations by offering a virtual workplace that can be accessed from any location at any given moment. The implementation of remote work policies and the cultivation of a flexible work environment enables workers to effectively manage their time, leading to enhanced production levels and a better balance between work and personal life [56]. The use of this adaptable approach also alleviates the limitations imposed by conventional office arrangements while enhancing more effective utilization of shop floor space. Efficient MVE offers virtual simulations that facilitate workers in the analysis of real-world circumstances, acquisition of new skills, and participation in virtual training programs [57]. This approach enables workers to efficiently use their knowledge in their daily duties, thus enhancing their performance outcomes. MVEE has the potential to be used in the context of virtual project management, facilitating the optimization of job distribution, team synchronization, and monitoring of project advancement. This will allow an organization to detect bottlenecks within a project, optimize project procedures, and enhance productivity. Therefore, the research can hypothesize that:

H4: MVEE has a positive association with PO.

2.6. Metaverse environment efficacy and innovations in organizations

The MVE offers a comprehensive and engaging platform that utilizes AR and VR technologies. This platform enables workers to actively engage with and evaluate the real-time performance of goods, facilitating informed decision-making processes [58]. This provides opportunities for workers to engage in experimentation, conduct tests on novel concepts, and produce prototypes within a regulated environment. This will encourage staff to devise inventive answers to corporate difficulties [59]. The use of virtual prototyping and iterative design within the context of MVE guarantees the achievement of IO [60]. The use of the virtual platform inside the MVE facilitates the organization's ability to access global knowledge, foster collaboration with international experts and leaders, and facilitate discussions on new ideas. This, in turn, contributes to the advancement of innovative practices within the organization [1]. The efficient implementation of MVE inside an organization will provide a conducive environment for fostering innovation. This approach enables workers to engage in collaborative efforts and actively contribute to the organization's innovation objectives [61]. Therefore, the study can hypothesize that:

H5: MVEE has a positive association with IO.

Based on the previous discussion, the study proposes a hypothesized model to illustrate the association of AIU, IoTU, and BDAU, with MVEE, and the association of MVEE with PO, and IO along with the hypotheses proposed in the previous section (refer to Figure 1).

3. Research Methodology

The study adapts a research methodology from two studies, Bawack et al. [62] and Wong et al. [63]. This research implements a multi-method, which includes partial least squares structural equation modeling (PLS-SEM), fuzzy-set qualitative comparative analysis (fsQCA), and artificial neural networks (ANN). A detailed methodological flow chart is presented in Figure 2.

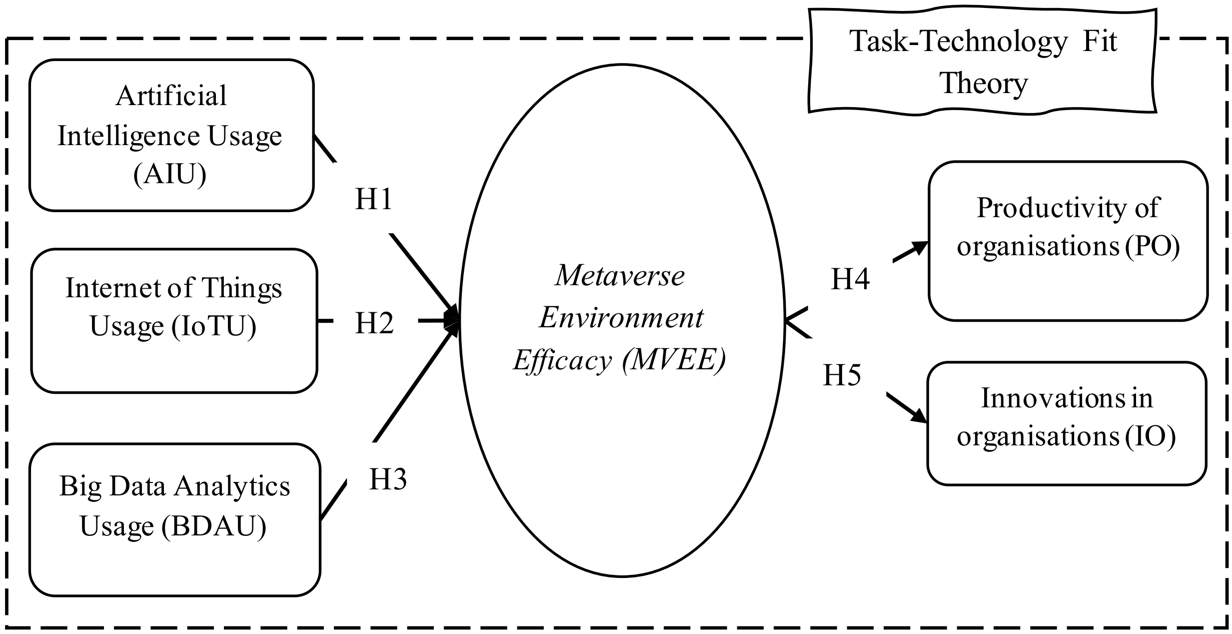

Figure 1: Proposed hypothesized model

3.1. Questionnaire development and data collection

The study encompasses comprehensive interviews conducted with executives representing various sectors within the gaming, information technology (IT), and entertainment industries. The initial section of the interviews involves questioning on diverse subjects about the adoption and implementation of digital technology usage, including AIU, IoTU, and BDAU for MVEE, to improve IO and PO. The authors also enquire about thoughts on the function of MVEE and its potential association with the IO and PO when actions are undertaken with a focus on MV. The emerging element of the study plan logically ensues from the consensus. The subsequent section of this study undertakes a critical analysis of the hypotheses by conducting a discussion. These discussions focus on the significance of different tasks that are the subject of digital technology adoption and the successful implementation of AIU, IoTU, and BDAU. The outcome of adoption and implementation is the establishment of a sustainable MVEE, facilitating the delivery of IO and PO. There is a consensus that utilizing AI, IoT, and BDA can greatly enhance the efficiency of MVE and contribute to advancements in IO and PO. The hypotheses are supported by academic literature, fostering confidence in the research.

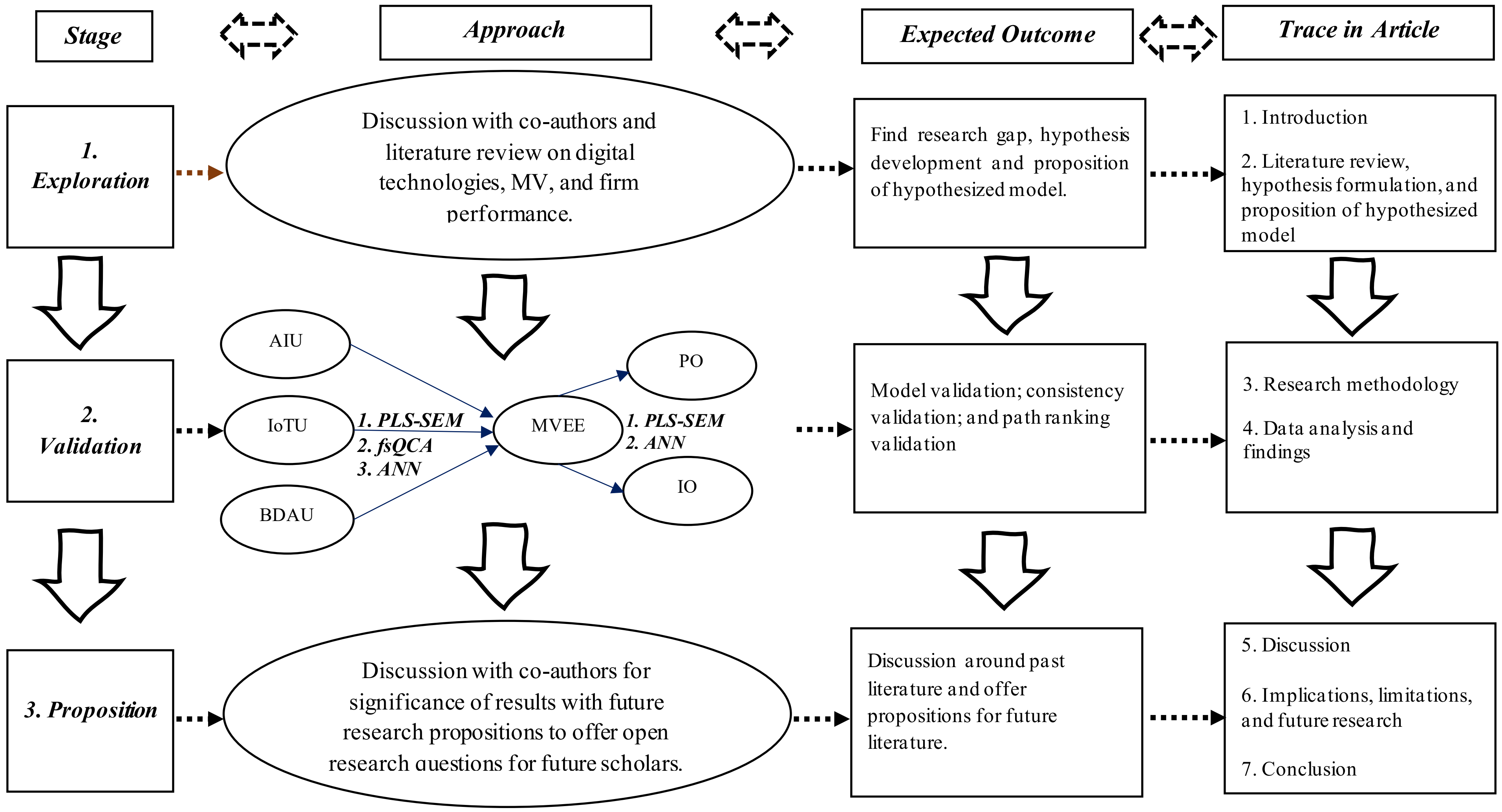

Figure 2: Research methodology flow chart

Subsequently, the questionnaire design is based on the proposed hypothesis model, as depicted in Figure 1. The research uses a 5-point Likert scale from 1 to 5, where 1 represents ‘strongly disagree’, and 5 represents ‘strongly agree’. The questionnaire aims to gather data from businesses in the IT, gaming, and entertainment sectors that have effectively incorporated and utilized AI, IoT, and BDA for efficient MVE. We have chosen these industries as the IT sector is crucial to enable the economy to expand rapidly and to offer millions of employment opportunities. Further, by 2025, it is expected that India's IT and business services industry will be worth $19.93 billion in US dollars[3]. In addition, foreign governments have invested heavily in the sector. The average Indian gamer now spends between 8.5 and 11 hours per week playing video games, making the sector a rising powerhouse in the battle for consumers' time and money[4]. Also, by 2028, the Indian gaming industry may be worth $8-10 billion yearly[4]. India has become the world's second-largest gaming market, with over 400 million players in 2022, up 40 million from the previous year[4].

Further, to pretest the questionnaire, we have requested our research team and industry experts to provide feedback regarding the comprehensibility of questions and any difficulties encountered while formulating their responses. This involves completing a preliminary version of the questionnaire, which is subsequently used in the later survey research. As a result of this procedure, several questions in the draft questionnaire are either rephrased or eliminated (refer to supplementary file Table A) and from an initial identified thirty five items, twenty five items are finally used. After that, to validate the measures in questionnaire, we have conducted pilot study, where through a simple random sampling method, the data was collected from the respondents, and factor analysis was conducted to test the reliability and validity of the items to confirm whether these items are defining constructs properly or not. In addition, it helps to select and confirm the suitability of constructs in the present settings. After conducting the analysis, the authors examine different measures of items and constructs to check if they are reliable and valid. This shows that the outcomes indicate a significant factor loading for all items (more than 0.7 (threshold limit)) [64]. Also, other parameters for constructs, such as “Cronbach's alpha, average variance extracted (AVE), and the Heterotrait-Monotrait ratio (HTMT) ratio”, are considered to be satisfactory (refer to

[3] https://www.gavstech.com/contribution-of-the-it-industry-in-indias-gdp/ (Accessed on 01/11/2023)
[4] https://timesofindia.indiatimes.com/blogs/voices/game-on-the-expanding-gaming-industry-in-india/ (Accessed on 01/11/2023)

supplementary file Table B and Table C) [65]. The outcomes of the initial survey show the validation of the questionnaire and confirm its reliability, allowing us to continue the research appropriately.

Once the measures of the questionnaire are validated, we have started collecting data for the final study. To mitigate the potential for biased outcomes and derive more comprehensive insights from this analysis, the authors endeavor to collect data from a diverse array of IT, gaming, and entertainment industries operating within the burgeoning Indian economy (refer to supplementary file Table D). A study was conducted from December 2022 to June 2023, focusing on Indian IT, gaming, and entertainment industries that employ AIU, IoTU, and BDAU for MVEE.

3.2. Non-response bias

After following the rigorous process of data collection, the research team collected a total of 132 responses (refer to supplementary file Table D). The investigation involves the utilization of a student's *t*-test to identify indications of non-response bias. A *t*-test is conducted on two sets of data, the first set ranging from December 2022 to March 2023, with the second set from April 2023 to June 2023. Based on the findings from the two-set analyses conducted, it is determined that there are no statistically significant differences ($p > 0.05$) observed between the initial and final respondents in terms of the means of the theoretical constructs tested [65].

3.3. Common method bias

Common method bias (CMB) is a situation that arises from the measurement method employed in an SEM study rather than from the interconnectedness of latent variables within the model under investigation [66]. This bias can lead to shared variance among the indicators, to overcome this issue, Kock and Gaskins [67] discuss the generation of variance inflation factors (VIF) for all latent variables in a model. The presence of a VIF exceeding 3.3 is suggested as an indicator of pathological collinearity and a potential indication that a model may be affected by common method bias [66]. Hence, if the values for all VIF obtained from a comprehensive collinearity assessment are equal to or less than 3.3, it is reasonable to conclude that the model is devoid of CMB [66]. Table 2 indicates that all VIF values are less than 3.3, showing no CMB is present in this study. Further, Podsakoff et al. [68] found that social science research methodologies often use the CMB test, which involves collecting data from a single source at a particular point in time. When it comes to CMB, the state of self-reporting datasets gathered from the same period using the same questionnaires presents a challenge. To mitigate this issue, we have collected data from multiple sources in different time frames. Along with both methods, to mitigate the CMB issue, we have also rearranged the order of the issues in which they had occurred to reflect the context in which they had occurred [69].

3.4. Assessment of measurement and structural model

Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to assess the validity of the proposed hypothesized model. The authors complete PLS-SEM with two processes (i.e. measurement and structural model evaluations) to confirm and verify the structure of the proposed model [70]. This allows confirmation and validation of the structure of the hypothesized model. Each of the items has a factor loading greater than 0.7. In addition, the values of the average variance extracted (AVE) are higher than the suggested cut-off value of 0.5; the values of the composite reliability (CR) and rho_A are higher than 0.7 [70, 71] (refer to Table 2). The assessment of discriminant validity involves examining the correlation coefficients between each construct and the square roots of their respective average variance extracted (AVE) scores. The Heterotrait-Monotrait Ratio of Correlations (HTMT) is utilized to evaluate the discriminant validity. The HTMT values for all variables in the model are found to be below the recommended cut-off value of 0.85 [70], indicating that the model exhibits acceptable discriminant validity (refer to Table 2). The predictive capability of the structural model is evaluated by assessing the R^2 and Q^2 values in the subsequent stage. The R^2 values and Stone-Geisser's Q^2 values are determined as follows: IO ($R^2 = 0.437$, $Q^2 = 0.347$), MVEE ($R^2 = 0.707$, $Q^2 = 0.560$), and PO ($R^2 = 0.420$, $Q^2 = 0.326$). The R^2 and Q^2 values provide evidence of satisfactory predictive validity of the structural model [70].

3.5. Asymmetrical modeling analysis

Fuzzy-set qualitative comparative analysis (fsQCA) is an asymmetrical modelling analysis based research method to examine several instances to elucidate a specific phenomenon within intricate contexts [72]. In contrast to symmetric modeling i.e. structural equation modeling, asymmetrical modeling (fsQCA) considers situations in which high values of one variable are either necessary, sufficient, or both to achieve high values of another [73]. This method serves as a valuable addition to traditional quantitative approaches since the latter often fail to capture the intricate causal relationships between variables [73]. It has formerly been used as a means to supplement the outcomes of hypothesized models that are first examined using SEM [74]. The integration of this method enables researchers to address the limitations of regression methods in testing hypotheses, hence facilitating the identification of novel and distinctive discoveries about the analysis of complex topics [75]. Furthermore, the propositions are developed for fsQCA analysis i.e. *the presence of at least one condition from AIU, IoTU, and BDAU is necessary for configurations that result in high MVEE, and there would emerge a configuration of necessary conditions, and a configuration of conditions which are sufficient from a combination of AIU, IoTU, and BDAU for better MVEE.*

This research uses fsQCA to investigate the processes that underlie the integration of AIU, BDAU, and IoTU for MVEE which were not previously identified via the use of PLS-SEM. The present study focuses on examining the specific configurations of AIU, BDAU, and IoTU that result in enhanced IO and PO. The items with interval scales are converted to fuzzy sets for use in fsQCA analysis. Calibration of the variables is required to find the optimal settings for delivering a satisfactory experience to customers. There is often uncertainty about membership at the crossover point of 0.5 [76], with calibration scores ranging from 0 (non-membership) to 1 (full membership). The factors were calibrated by three important thresholds: a whole set membership threshold of 0.95, a full set non-membership threshold of 0.05, and a cross-over point threshold of 0.5 [77].

Table 2: Psychometric analysis and measurement model assessment

	Cronbach's alpha (α)	rho_a	Composite reliability (CR)	AVE	Discriminant Validity (HTMT)						SRMR	0.041	
						AIU	BDAU	IO	IoTU	MVEE	R^2	Q^2	*VIF*
AIU	0.907	0.909	0.935	0.782	**BDAU**	0.760					-	-	**AIU → MVEE** (2.593)
BDAU	0.928	0.930	0.949	0.823	**IO**	0.683	0.619				0.437	0.347	**BDAU → MVEE** (2.146)
IO	0.941	0.942	0.955	0.810	**IoTU**	0.804	0.717	0.648			-	-	**IoTU → MVEE** (2.349)
IoTU	0.904	0.908	0.933	0.776	**MVEE**	0.845	0.803	0.708	0.797		0.707	0.560	**MVEE→ IO** (1.000)
MVEE	0.921	0.922	0.944	0.808	**PO**	0.671	0.628	0.846	0.658	0.695	0.420	0.326	**MVEE → PO** (1.000)
PO	0.923	0.931	0.945	0.812									

We computed the 95th, 50th, and 5th percentiles of our measurements using percentiles so that we could find the data values that corresponded to the criteria. The thresholds determined for the 95th, 50th, and 5th percentiles had an average value of 4, 3, and 2, respectively. Firstly, a truth table is constructed from the fuzzy data to determine which configurations will be analyzed. Next, the necessary causal conditions and desired outcomes are specified. To indicate the amount to which a causal solution leads to an event, the configurations chosen in this research (consistency) account for at least 80% of the instances. The result may be explained by combinations that reach this level of consistency. The degree to which any solution consistently adopts results with great customer experience performance is quantified using solution consistency [78]. By assessing the "raw, unique, and solution coverage" [76], the empirical significance of each solution is established. Raw coverage quantifies the fraction of the outcome's membership that can be attributed to each solution word.

The percentage of memberships in the result that can be attributed to a single solution term, as measured by unique coverage, is a quantitative indicator of solution term importance [78]. Solution coverage quantifies the fraction of memberships in the result that can be accounted for by the whole solution.

3.6. Robustness testing of hypotheses

As structural equation modeling (SEM) can only find linear associations, they are unable to understand the complexity of human making decision systems [79]. Further, SEM assume that changes in one variable may be offset by changes in another variable, with the use of a linear equation connecting the exogenous and endogenous factors. Since Artificial Neural Network (ANN) can capture both linear and nonlinear interactions inside a non-compensatory model, it may be conducted to overcome the limitation of PLS-SEM analysis by solving this issue [80]. "Noises, non-normality of distribution, homoscedasticity, nonlinearity, and multicollinearity" are all things that ANN models can handle better than linear models [81]. Due to a better prediction accuracy, ANN models surpass more traditional statistical methods (such as MRA, and SEM) [82]. Therefore, the authors couple SEM with ANN by using the important predictors obtained by the PLS-SEM method as input neurons for the ANN models [83] so that they may better support one another. Each ANN model has an input layer, a hidden layer, and an output layer [84]. Root mean square errors (RMSE) and normalized significance of the input neurons are calculated using the feed-forward-back-propagation method and multilayer perceptrons [81]. The use of a feed-forward-back-propagation method facilitates the training of the network to achieve precise predictions or classifications via the modification of the synaptic weights connecting the neurons. A cross-validation technique, known as 10-fold cross-validation, is employed, wherein 90% of the available data is utilized for training purposes, while the remaining 10% is reserved for testing. The present research uses this ANN model due to its inherent simplicity and interpretability in comparison to more intricate structures such as deep neural networks. Interpretability assumes a critical role in some instances, particularly within domains that are governed by regulatory or ethical considerations, such as healthcare or finance. Additionally, this ANN model may exhibit a reduced dependency on data points and processing resources in comparison to their more modern counterparts. When confronted with a scarcity of data, opting for a less complex ANN model might be a pragmatic decision.

4. Results and findings

The findings from PLS-SEM indicates that all validity and reliability measures pass their respective cutoffs. Cronbach's alpha and the composite reliability measure both exceed the critical value of 0.70. Additionally, AVE values are higher than the cut-off value of 0.50. Therefore, the reliability and validity metrics for both the items and the constructs are confirmed (Table 2). According to the Fornell-Larcker criteria (Table 2), latent variables have discriminant validity if the square root of the AVE of each construct is larger than its maximum correlation with other constructs. Furthermore, the HTMT pairings of latent variables are all lower than the cut-off of 0.85 (Table 2), demonstrating discriminant validity.

Furthermore, Table 2 presents a comprehensive overview of the structural model derived from the PLS-SEM assessment. It includes the path coefficients, their corresponding degrees of significance, and the extent to which the model explains the variance of the dependent variables (R^2). The model presented accounts for 43.7% of the variability seen in IO, 42% of the variability observed in PO, and 70.7% of the variability observed in MVEE. To evaluate the adequacy of the model, the standardized root mean square residual (SRMR) value is calculated. This value represents the discrepancy between the sample covariance matrix and the model covariance matrix. According to Henseler et al. [85], an SRMR value of 0.08 is considered an appropriate threshold for PLS path models. Therefore, the SRMR value of 0.041 achieved in this investigation indicates that the model satisfies the fit condition. Lastly, the assessment of hypothesis results for all relationships in the structural model is conducted using confidence intervals bias. The data is assessed using 10000 bootstrapping resamples in PLS-SEM [59] (refer to Table 3). The results indicate that the standard coefficients and p-values exhibit statistical significance for all the observed relationships (refer to Table 3).

Table 3: Summary of hypothesis testing

Path relation	*B*	SD	*t*-statistics	*p*-values	Hypothesis	Decision
AIU → MVEE	0.361	0.112	3.216	0.001	H1	Supported
IoTU → MVEE	0.253	0.086	2.927	0.003	H2	Supported
BDAU → MVEE	0.326	0.096	3.406	0.001	H3	Supported
MVEE → PO	0.648	0.075	8.664	0.000	H4	Supported
MVEE → IO	0.661	0.079	8.402	0.000	H5	Supported

AIU substantially associates with MVEE (β = 0.361; t = 3.216, significance at $p < 0.05$). Moreover, the IoTU positively associates with MVEE (β = 0.253; t = 2.927, significance at $p < 0.05$), while BDAU also positively associates with MVEE (β = 0.326; t = 3.406, significance at $p < 0.05$). The MVEE also exerts a positive association with both PO (β = 0.648; t = 8.664, significance at $p < 0.05$) and IO (β = 0.661; t = 8.402, significance at $p < 0.05$). Therefore, the findings suggest that hypotheses H1, H2, H3, H4, and H5 are all supported.

After the structural model analysis, we have looked into the findings from fsQCA analysis, where the presented truth table (refer to supplementary file Table E) about the MVEE outcome demonstrates that to achieve a consistency level greater than 0.80, it is necessary for all antecedents (i.e. ingredients) to exhibit full membership [62]. Nevertheless, assessing the coherence and comprehensiveness of all the recipes that encompass varying quantities of antecedents is imperative. Further, the solutions from necessary condition analysis (refer to supplementary file Table F), indicate that AIU, IoTU, and BDAU are necessary for MVEE, as all values are above the threshold of 0.90 [76]. In addition, the findings of fsQCA created three possible combinations of causal conditions that led to MVEE (see Table 4), where the black circle (●) interprets as conditions presence and blank space means that the outcome variable is not associated with conditions. The consistency and coverage for all potential configurations are determined by prioritizing the use of an intermediate solution [64,85]. Furthermore, the consistency and coverage of all potential configurations are determined by identifying the configurations that meet the criteria of having a coverage greater than 0.20 and a consistency greater than 0.80 [86] (refer to Table 4). The outcomes from the fsQCA approach (consistency > 0.80; coverage > 0.20) for AIU, IoTU, and BDAU indicate consistency with PLS-SEM findings; this further suggests that AIU, IoTU, and BDAU are significantly associated with MVEE. The solution obtained via fsQCA has a high level of consistency (0.98357) and exhibits substantial coverage (0.97202).

Table 4: Sufficient conditions configurations

	INTERMEDIATE SOLUTION		
Configurations	**Solutions**		
	1	**2**	**3**
AIU	●	●	
IoTU	●		●
BDAU		●	●

Raw coverage	0.88949	0.88498	0.87460
Unique coverage	0.05097	0.04646	0.03607
Consistency	0.98551	0.98840	0.98577
Solution coverage	0.97202		
Solution consistency	0.98357		

Further, we have investigated the findings from ANN analysis. The power of predictors in ANN models is presented (refer to supplementary file Table G). To evaluate the association of individual predictors with the development of MVEE, IO, and PO, a measure of normalized importance is computed. This measure is derived by calculating the relative importance of each predictor and dividing it by the highest relative importance value observed among all predictors in each ANN model, as outlined in the study conducted by Leong et al. [86]. The findings suggest that the variable AIU exhibits the highest level of predictive capability concerning the variable MVEE, with BDAU as the second highest and IoT following closely behind. AIU (Independent Variable 1), IoTU (Independent Variable 2), and BDAU (Independent Variable 3) are the sole predictors for MVEE (Dependent Variable 1); MVEE (Independent Variable 4) is the sole predictor of PO (Dependent Variable 2) and IO (Dependent Variable 3).

Table 5: Comparative analysis between PLS-SEM and ANN

PLS-Path	β	ANN results: Normalised relative importance (%)	Ranking of independent variables (PLS-SEM)	Ranking of independent variables (ANN)	Remark
MVEE as an output (Model A)					
AIU→MVEE	0.361	100	1	1	Consistent
IoTU→MVEE	0.253	76.79	3	3	Consistent
BDAU→MVEE	0.326	79.65	2	2	Consistent
PO as an output (Model B)					
MVEE→PO	0.648	100	1	1	Consistent
IO as an output (Model C)					
MVEE→IO	0.661	100	1	1	Consistent

Table 5 presents a comprehensive ranking and comparative analysis of the noteworthy predictors within the hypothesized model. The ranking outcomes of PLS-SEM are determined through the examination of path coefficients. On the other hand, the ranking of ANN models is established by utilizing normalized relative importance. According to Model A, Model B, and Model C, AIU, IoTU, BDAU, and MVEE rankings are consistent and do not differ between the PLS-SEM and ANN models. This suggests the presence of latent factors that suggest the roles of MVEE, PO, and IO in practical contexts where a linear perspective can fully explain the relationship between variables.

5. Discussion

This research examines the association between the use of emerging digital technologies (AIU, IoTU, BDAU), MVEE, PO, and IO using TTF as a theoretical foundation. The study uses a combination of methods, including PLS-SEM, fsQCA, and ANN. The results demonstrate a strong and reliable pattern of relationships, offering important perspectives on the association of digital technologies with MVEE and its consequent implications for organizational outcomes. The research begins by presenting a hypothesized model that delineates the association among AIU, IoTU, BDAU, MVEE, PO, and IO. Subsequently, the model is subjected to empirical testing using PLS-SEM. The empirical validation of the first hypothesis posited that AIU has a positive association with MVEE. The assertion is supported by the statistically significant standard coefficient, as seen in Table 3. To enhance the reliability of the results, the study expands the analysis to include fsQCA. The findings from both PLS-SEM and fsQCA demonstrate a substantial level of congruity. The presence of consistency between two distinct analytical procedures enhances the credibility of the relationship created within the research. This provides more evidence of the association of IoTU and BDAU with the MVEE. Validation of the second and third hypotheses provides evidence in favor of the notion that both IoTU and BDAU have a positive association with the MVEE. The results presented in this study are supported by previous research [44, 46, 47, 51, 53] indicating their consistency with already established knowledge. The research expands its scope to investigate the relationships between the MVEE and two significant organizational outcomes, PO and IO. The findings confirm that the efficient MVE has a considerable positive association with both PO and IO. The result underscores the significance of MVEE in promoting productivity and innovation results. This is consistent with previous research [1,57] and established theoretical models.

After that, we have tested our propositions through fsQCA analysis. The first proposition, i.e., "*The presence of at least one condition from AIU, IoTU, and BDAU is necessary for configurations that result in high MVEE*" is supported by the solution from necessary conditions (refer to supplementary file Table

F). The outcomes from Table F suggest the necessity of at least one digital technology (AIU/BDAU/IoTU) as a positive association with MVEE. Further, the second proposition, i.e., "*There would emerge a configuration of necessary conditions, and a configuration of conditions which are sufficient from a combination of AIU, IoTU, and BDAU for better MVEE"* is supported by the solution from necessary conditions (refer to supplementary file Table F) and sufficient conditions configurations (see Table 4). In all solutions from Table 4, the digital technologies (AIU, IoTU, and BDAU) are present as a core condition. This finding does not only prove that digital technologies (AIU, IoTU, and BDAU) are associated with MVEE but also that they are necessary conditions for MVEE [44, 46, 47, 51, 53]. To be specific, solution 1 can apply to the gaming, information technology, and entertainment firms where they can achieve efficient MVE to carry out their operations without considering the effective use of BDA, but they seek AIU and IoTU, to deliver IO and PO. These might speak for the firms who want to integrate AI and IoT for seamless and interactive experiences in MVE to foster innovation and improve the productivity of the user without considering the significant role of using BDA. Further, solution 2 is more suitable for different gaming, information technology, and entertainment firms to carry out their operations in the efficient MVE without implementing IoTU, but in addition to seeking AIU and BDAU, to achieve IO and PO. The firms that are more focused on user behavior and prediction of actions based on the previous data and want to mimic the repeated task might use this solution to achieve IO and PO, without considering the significant use of IoT devices in their ecosystem. The third solution presents those gaming, information technology, and entertainment firms who carry out their operations in the efficient MVE without considering the effective use of AI, but they seek IoTU and BDAU, to get IO and PO. This solution might present the firms who integrate IoT for smart devices and BDA for optimizing and predicting behaviors for enhancing multiuser experience in efficient MVE to deliver innovation as well as better productivity without requiring the use of AI. This way, fsQCA not only validates the findings from the structural model by supporting the various hypotheses tested by PLS-SEM, but it also complements these findings by offering various configurations (combinations of conditions) of AIU, IoTU, and BDAU that are sufficient and necessary for MVEE.

Furthermore, the study evaluates the comparative significance of AIU, IoTU, and BDAU with MVEE. The findings suggest that the association of AIU with MVEE is the most significant, followed by BDAU, while the association of IoTU is comparatively less. The results from both PLS-SEM and ANN demonstrate a consistent alignment, providing further support to the conclusions drawn. The use of multi-data analysis methodologies, such as PLS-SEM, fsQCA, and ANN, emphasizes the thorough and meticulous nature of the investigation. The congruity of findings across different methodologies offers substantial support for the postulated theoretical framework, bolstering the research's capacity for prediction and explanation. Furthermore, this research makes a substantial contribution to the comprehension of the dynamic relationships among digital technologies, the virtual environment, and the results of organizations. This study provides empirical evidence supporting the positive association of AIU, IoTU, and BDAU with the MVEE, along with resulting improvements in organizational productivity and innovation. The robustness of the results is strengthened by the consistent findings obtained using multi-analytical methodologies, thus enhancing the dependability of the outcomes. These findings highlight the possibility for implementation of these technologies in organizational settings to achieve favorable outcomes. The utilization of a multi-method strategy, together with its alignment with previous research, establishes a robust basis for future investigations in this field. Consequently, it contributes to the development of our comprehension regarding the digital transformation of organizations in the efficient MVE.

6. Implications, limitations, and future research

6.1. Theoretical implications

The TTF theory implies that the effectiveness of technologies largely depends on the alignment with the tasks they are meant to promote [14]. The current analysis employs the TTF theoretical framework to explore the relationships between the AIU, BDAU, IoTU, MVEE, IO, and PO. Particularly, we explore the theoretical implications of TTF in the context of the MV and how the TTF can significantly enhance the understanding and application of digital technologies. Automation of the standard and repetitive work is one of the manners that AIU has a considerable association with the efficiency of tasks [87]. Furthermore, AIU might carry out repeated activities in the MVE as such the users, especially gamers, can focus on their innovative and challenging tasks. This goes in line with TTF's explanation that effective utilization of technology occurs when an individual is capable of finishing a task more resourcefully [20]. AIU tends to increase user interaction by tailoring cognition to a user's specific inclinations and ensuring that users are capable of undertaking activities in a more efficient way [7]. Further, IoTU collects and analyzes data to allow users to work more efficiently in the MVE [50]. Which, TTF's fact that IoTU functions in offering real-time data enable work performance as users can create well-informed decisions [10]. The efficient MVE enables the efficient handling of resources through the seamless connectivity that exists between the digital and physical domains [10]. The administration of resources is managed, which in turn maximizes resource utilization and enhances the overall productivity of an individual.

The possible effect of BDAU to analyze considerable volumes of data and provide insights for potential implementation coincides with the focus TTF aims to have on enhancing task performance. With the opportunity to analyze the performance of users and change the allocation of resources based on that assessment, BDAU helps to support the principles of dynamic decision-making in the MVE [13]. Importantly, because there is empirical validation through BDAU, the decisions will be data-driven, which helps to enhance the effectiveness of the MVE in general [52]. Inherently, the MV is an interactive space designed to simplify numerous applications. The utilization of the MV increases information exchange, collaboration, and, in turn, performance [88]. Because of the contributions of AIU, IoTU, and BDAU, the MV can streamline meetings, teamwork efforts, and educational ventures. Furthermore, the TTF theory implies that technology is beneficial if it is compatible with tasks and processes [20]. In this situation, the immersive platform of the MV can improve and support various tasks because, in the end, it contributes to individual and organizational performance [55]. The MV offers the ability to experiment, take risks, and follow iterative processes. The TTF theory also suggests that the use of technology can support the potential of tasks, and in the MV, technology helps to sustain an ecosystem where development is continuous, and feedback is quick. Because of this approach to problem-solving and creation, new ideas appear regularly and, due to efficient approaches, add to the possibility of task success when they are traced through the feedback provided by the efficient MVE [1]. Organizations can optimize even more efficiency and innovation by combining AIU, IoTU, and BDAU for MVEE. Furthermore, the MV is the prime example that clearly shows how it may drive innovation and support an organization's success [61]. Being a testbed, the efficient MVE stimulates experimentation and supports recombination. As a result, a decision can be reconsidered at any time enabling the dynamic approach to the choice of available alternatives [58]. To this end, TTF proves to be the right foundation for understanding how such technologies as AIU, IoTU, and BDAU can enhance organizational outcomes and task efficiency. Also, TTF is supported by the dynamic approach as well as the possibility of combining various technologies present in the MVEE. For this reason, the efficient MVE is a great location for companies that want to optimize efficiency and creativity.

6.2. Practical implications

The practical implications of the research findings are multi-faceted, featuring numerous dimensions of technology implementation, user experience enrichment, organizational efficiency, and work dynamics. The incorporation of AI-powered virtual assistants within the MVE can greatly enrich the user experience, providing personalized directions, suggestions, and recommendations following user preferences and prior interactions [8]. Consequently, this customization amplifies user engagement and satisfaction with the MVEE, rendering it a more immersive and personalized space for user exploration within virtual environments [9]. Meanwhile, AI algorithms can assist in timely decision-making by analyzing real-time data from the MVE, and monitoring user behavior and environmental changes to impart data-based insights and recommendations, this enhances the informed and effective nature of decision-making processes [7]. Also, the integration of IoT within the MVE simplifies user collaboration and knowledge exchange through better knowledge systems among users. Virtual conference rooms within the MVE can be enhanced through the integration of IoT devices, which together with virtual conference room instruments, more thoroughly encompass the range of available artifacts for user collaboration. This ensures improved collaboration and tool appropriateness that enhance user productivity and effectiveness, particularly in regularly scheduled real-time virtual meetings and collaborative sessions [6]. Lastly, BDA analysis of large data volumes from the MVE can yield additional, evidence-based insights and recommendations [52]. By analyzing user interaction patterns and session themes, the MVE can yield personalized and session-based virtual event recommendations that will enable organizers to improve their from-event resource management and session customization. Better event programs, planning, and execution results. The MVEE reduces organizational time and costs by enabling virtual meetings, conferences, and collaborative sessions. Savings are made on the costs of the physical infrastructure required by face-to-face meetings. Participation of the full set of users in a meeting at any point in time is made easier [6]. The MVE's remote work capabilities give employees the flexibility to meet their obligations from any location with a network connection, providing an increased work-life balance, job satisfaction, and work productivity for both employees and their employers [83]. Moreover, the MVE can democratize collaboration by enabling access and involvement in knowledge systems to anyone with a network signal, obliterating geographical borders for collaboration, and fostering multidisciplinary creativity and input that yields innovation and new solutions. Benefits arise from the range of user perspectives and available expertise across a spectrum of subject matters and issues that have a bearing on individual, group, and organizational outcomes. Overall, the practical association of the AIU, IoTU, and BDAU with the MVE is profound and extensive, presenting broad implications for user experience enrichment, organizational efficiency, and collaborative innovation that currently show only a fraction of the transformative potential.

6.3. Methodological implications

A multi-method approach, including PLS-SEM, fsQCA, and ANN is employed to meet the objectives of this study, indicating an extremely thorough investigation into relationships among the variables. This methodology allows for a deeper investigation from several perspectives, strengthening the overall credibility of the results. Incorporating AIU, IoTU, BDAU, and the MVE requires expertise from a variety of fields. Collaboration and knowledge sharing among researchers and practitioners from other domains, such as computer science, data analytics, and organizational psychology, is essential for understanding the complex association of these technologies with organizational settings. Quantitative techniques like PLS-SEM and ANN are used extensively throughout the research; fsQCA is also included to show that the authors are cognizant of the need to include qualitative information. A more complete picture of the issue may emerge from the integration of statistical connections with nuanced, context-specific findings. This study can be strengthened by using a different cross-sectional technique, such as pilot testing.

Incorporating these methodological factors into the study will increase its rigor, relevance, and applicability, making it useful for both academics and practical applications in the commercial sector.

6.4. Limitations and future research

The present study makes a significant contribution in explaining the interaction among the usage of advanced digital technologies (AIU, IoTU, and BDAU), the emerging MVE, and its association with organizational outcomes (PO and IO). Still, there are limitations. Firstly, with a relatively modest sample size (n = 132), concerns related to the generalizability of findings are warranted. Increasing the sample size and diversification of participants will enhance the external validity and statistical power of the inferences. Secondly, the research appears somewhat skewed toward quantitative methods that largely overrule multi-faceted qualitative insights into complex interrelationships. Moreover, the absence of in-depth consideration of moderating variables and contextual factors associated with the described relationship implies that additional research should focus on the potential association of these variables. Similarly, the lack of a detailed discussion of control variables and the various issues, limitations, and unintended outcomes that may accompany the integration of digital technologies and the Metaverse into organizational settings undermines the generalizability and applicability of the described connections to other industries. For these reasons, future research should address the identified limitations, expanding the current knowledge of digital technology use within diverse organizations and contributing to both descriptive and prescriptive literature. Based on our findings, the authors have conducted a brainstorming session and proposed some open research questions for future scholars (refer to Table 6).

Table 6: Open research questions for future research, based on findings of the relationships among different constructs

Relationship between constructs	Open research questions (ORQs)
AIU → MVEE **IoTU → MVEE** **BDAU → MVEE**	*ORQ1:* What are the hazards to user safety and data protection that may arise from using AI-driven apps in the MVE, and how may these dangers be reduced? *ORQ2:* How may IoT devices and sensors be used in the MV to match tasks with available technologies better, and how might users benefit from access to real-time data and heightened situational awareness to increase their task effectiveness and overall experience?

	ORQ3: How can researchers utilize BDA to sift through massive volumes of MV user data and use the results to better inform practices in areas such as content development, social interaction, and the architecture of simulated worlds?
	ORQ4: What are the psychological effects of engaging with AI-controlled non-player characters (NPCs) in the MVE, and how can AI be programmed to produce genuine feelings in users?
	ORQ5: How can researchers combine IoT, AI, and BDA to explore unique methods for scalability and performance issues in large-scale MVE settings, thereby guaranteeing consistent user experiences across all available devices?
MVEE → PO	*ORQ6:* How can researchers best evaluate the qualitative and quantitative markers of increased productivity due to the widespread use of the MVE?
	ORQ7: How does the MVE facilitate interdisciplinary contact, leading to creative problem-solving and enhanced output?
MVEE → IO	*ORQ8:* How does the MVE help to inspire people to work together and exchange ideas, hence increasing the flow of creative solutions inside a company?
	ORQ9: How do workers' willingness to take risks and their level of imagination in the MVE associate with the company's innovation culture as a whole?
	ORQ10: Is there a way to utilize the MVE as a proving ground for ideas and developments before bringing them into the actual world?

7. Conclusion

This research conducts a thorough examination of the interactions among usage of advanced digital technologies, including AIU, IoTU, and BDAU, and their association with the developing MVEE, consequently associating with the outcomes of PO and IO. The study effectively validates and expands upon the proposed model by the use of a multi-method approach, including PLS-SEM, fsQCA, and ANN. The study not only validates the favorable association among AIU, IoTU, BDAU, and MVEE, consistent with previous research and theoretical models but also demonstrates the significant association of MVEE with both PO and IO. Additionally, the examination of several analytical methodologies underscores the strength and ability of the model to make accurate predictions, showcasing its reliability across PLS-SEM, fsQCA, and ANN analyses. These findings make significant contributions to the comprehension of the revolutionary potential of digital technologies in the efficient MVE. This is a sound basis for future initiatives aimed at leveraging this innovative environment to improve organizational productivity.

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Appendix

Abbreviation	Details
AI	Artificial Intelligence
AIU	Artificial Intelligence Usage
ANN	Artificial Neural Networks
AR	Augmented Reality
BDA	Big Data Analytics
BDAU	Big Data Analytics Usage
fsQCA	Fuzzy-set Qualitative Comparative Analysis
ICT	Information and Communication Technology
IO	Innovation in Organizations
IoT	Internet of Things
IoTU	Internet of Things Usage
IT	Information and Technology
MV	Metaverse
MVE	Metaverse Environment
MVEE	Metaverse Environment Efficacy
PLS-SEM	Partial Least Squares Structural Equation Modeling
PO	Productivity in Organizations
TTF	Task-Technology Fit
VR	Virtual Reality