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Industrial Internet of Things and Emerging Digital Technologies–Modeling Professionals' Learning Behavior

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ABSTRACT Industrial internet of things (IIoT) and digital technologies have been evolving fast, leading to a challenge in the availability of skills and commotion in job profiles. While existing job profiles are changing, new job profiles are getting created. Professionals face the challenge of obsolescence and pressure for continuous reskilling and prepare for the future of work. The fast-changing innovations in digital technologies of IIoT like the internet of things, robotics, augmented reality, artificial intelligence, and big data analytics trigger in-depth analysis of professionals' learning behavior. This study extends the individual's ambidextrous learning theory and unified theory of acceptance and use of technology (UTAUT) to develop a quantitative behavioral model Learning Emerging Digital Skills (LEDS). LEDS model describes the antecedents of professionals' learning behavior towards fast-changing emerging digital technologies involved in IIoT. A nation-wide structured survey of 685 professionals across 95 firms in India across industry sectors engaged in IIoT product and solution development in sectors like automotive, aerospace, healthcare, and energy were undertaken. Findings from structural equation modeling are validated via a qualitative study. Social influence and personal innovativeness, anxiety, long-term consequence, and job relevance affect behavioral intention to learn. Professionals' performance level and technology preference moderate the relationship between antecedents and the intention to learn. For exceptional performers, personal innovativeness is the key driver in the intention to learn. For average performers, social influence and anxiety are additional significant factors towards intention to learn. Technology itself moderates the learning behavior, which indicates professionals' preference to learn a technology over the other based on technology maturity and use potential. This study can help practitioners design ramp-up strategies to meet the current and future demand of emerging digital skills to meet their IIoT strategy. Policymakers can use antecedents of employees' ambidextrous learning behavior to formulate policies to achieve ambidextrous organization's goals.

INDEX TERMS Industrial IoT (IIoT), emerging digital technology, ambidextrous learning behavior, learning of emerging digital skills (LEDS), future of work.

I. INTRODUCTION

Industrial production is being transformed due to the integration between the physical world and the digital world. In Germany, this was termed Industry 4.0 and as industrial IoT (IIoT) in the USA. IIoT provides a fusion of intelligent, interconnected systems of IoT devices to provide a higher level of availability and scalability. In the last few years, IIoT or Industry 4.0 has drawn interest in both academic and industry. Studies have pointed out that this transformation will lead to a broad societal discourse, impacting the future of work and the role professionals are expected to play. The transformation will be accompanied by a social change in staffing requirements, workload, competition for jobs, and job security [1]. Realization of IIoT solutions include advanced digital skills [2] like IoT, robotics, big data analytics, cybersecurity, augmented reality (AR), virtual reality (VR), artificial intelligence (AI), and machine learning (ML). Moreover, talent is scarce in these skills.

Several published industry reports from McKinsey Global Institute [3], Boston Consulting Group [4], Capgemini and LinkedIn [5], and World Economic Forum [6], [7]

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acknowledge that the skill gap exists, and the gap is growing. As per these reports, a considerable gap exists in professionals' current skills and what they need in future roles. New jobs will be created, whereas there is a risk of losing current jobs. As digital technologies evolve, an individual's ability to learn and acquire new skills and expand their capabilities is vital. Hence, there is an urgent need to understand the impact of the fast-changing era of industrial IoT and digital technology on the labor market.

In this fast-changing technological environment, industrial sectors (like industrial, manufacturing, automotive, aerospace, energy, healthcare, oil & gas) are moving towards IIoT products and solutions. Professionals feel a constant threat of large-scale unemployment and professional obsolescence [8] due to technological advancements that could disrupt the labor market. Professionals need to cope with the technological advancements by continuously develop new knowledge [9] and involve in knowledge renewal [10]. Focus on skill development is necessary [11], which integrates market needs and new technologies [12].

A. PROBLEM STATEMENT

Rapid technology change is handled by the organization's ambidextrous strategy [13]. Ambidextrous organizations simultaneously pursue current knowledge for survival in the current business and explore new knowledge for growth. At the individual level, the employees' ambidextrous learning behavior [14] involves simultaneously exploring and learning new skills whereas exploiting current skills used in the current project. If employees are not aligned with the organization's ambidextrous strategy, then investment in skilling programs leads to low return. As a result, no significant change in the challenge of talent scarcity. So, the key question is, how do we address the misalignment between an organization's ambidextrous strategy and employee's non-ambidextrous behavior? Hence, there is a need to analyze and understand professionals' ambidextrous learning behavior in the complex and dynamic environment of IIoT and emerging digital technologies.

Previous research received significant focus on the realization of organizations' ambidextrous strategies. Recent research shows individual ambidexterity's impact on individual and group performance [15], [16]. However, there is very little scholarly focus on employees' ambidextrous learning intention and learning behavior in technology's fast-changing world. So far, none of the studies have focused on this aspect. Hence, it is imperative to analyze professionals' learning orientation and ambidextrous learning behavior. Understanding the antecedents of professionals' learning behavior towards fast-changing technology will help align HR policies. With this, organizations can address the critical success factor in achieving significant results from their ambidextrous strategy.

Additionally, the technology acceptance theories and structural equation modeling technique is used in different contexts to study acceptance behavior [17]. However, research on the behavioral intention and actual behavior in the context of emerging digital technologies is sparse. Moreover, understanding this behavior is critical for developing and deploying industrial IoT solutions.

In the context of an ambidextrous organization involved in developing products and services involving IIoT solutions, the answer to our key question lies in understanding three critical aspects of professionals' learning behavior towards emerging digital technologies. So, we arrived at the below questions.

RQ1: What are the determinants of intention to learn and actual learning behavior of professionals towards emerging digital technologies?

RQ2: What is the moderation effect of performance level, gender, and technology on the antecedents of professionals' intention to learn emerging digital technologies?

RQ3: In the context of emerging digital technologies, how does intention to learn impact actual learning behavior?

B. KEY CONTRIBUTIONS

An empirical study was conducted based on a nation-wide survey in India to analyze the learning orientation and learning behavior of professionals towards learning digital skills of IIoT. This study's key contribution is developing the Learning of Emerging Digital Skills (LEDS) model. LEDS is derived from ambidextrous learning theories [14] and technology acceptance theories.

As per the LEDS model, social influence and personal innovativeness, anxiety, long-term consequence, and job relevance affect behavioral intention to learn. Behavioral intention influences the actual learning behavior; gender, performance level, and technology preference are identified as moderators that affect the relationship between antecedents and the intention to learn. Female employees' relationship between intention to learn and actual learning behavior is much more robust than their male colleagues. For exceptional performers, personal innovativeness is the key driver in the intention to learn. For average performers, social influence and anxiety are additional significant factors towards intention to learn. Technology itself moderates the learning behavior, which indicates professionals' preference to learn a technology over the other based on technology maturity and use potential.

Understanding professional's learning behavior towards emerging digital technologies would help practitioners anticipate the challenges while ramping up large teams. Recommended policy alignments will help meet the current and future demand of talent for IIoT solutions involving emerging digital technologies. This study can help practitioners design ramp-up strategies to meet the current and future demand of emerging digital skills required to meet their IIoT strategy. Policymakers can use antecedents of employees' ambidextrous learning behavior to formulate policies to achieve ambidextrous organization's goals.

C. STRUCTURE OF THE PAPER

This article includes sections on the literature review, the methodology employed, data analysis, and findings. Lastly, we highlight the contribution to theory and practice, followed by limitations of the study and future research scope.

II. THEORETICAL BACKGROUND

The demand for skilled professionals required for developing IIoT products and services exceeds the supply [18]. However, none of the previous research explains professionals' behavior in learning and using emerging digital technologies required for IIoT. To match the fast development in emerging digital technologies, professionals must continuously develop new knowledge [9]. Our research aims to study professionals' learning orientation and ambidextrous learning behavior towards digital technologies of IIoT solutions. Hence, we reviewed the literature related to digital technologies of IIoT, ambidextrous theory, learning motivation theories, and technology adoption models.

A. INDUSTRIAL IoT AND EMERGING DIGITAL SKILLS

The fourth industrial revolution has brought a paradigm shift due to the integration of internet technologies with industry [19]. The critical elements of the integration revolve around an affordable communication system in the industry setup since field devices like machines, plants, tools will all be connected to the network. Physical devices will have a second identity in the virtual form of data and models. As per the systematic literature review of IIoT [20], world-wide spend on the internet of things by 2021 is forecasted to be more than a trillion US dollars. A larger part of this spending will be across the US, western Europe, and Asia pacific. IIoT application areas like M2M (machine-to-machine communication), CPS (cyber-physical systems), and wireless sensor networks will get the highest focus.

A literature review about skill development in digital technologies identifies skills involved in developing IIoT solutions and digital transformation [21]. Emerging technology trends of IIoT include advanced digital technologies [2] like IoT, AI/ML, big data analytics, AR/VR, robotics, and cybersecurity [22], [21]. These emerging digital technologies are being integrated into organizations, resulting in various advantages. To name a few, reduced labor costs, shorter delivery time to market products, productivity growth, and higher product quality provides a safer environment to perform dangerous tasks. Also, having access to extensive data for analysis can help identify new products and services across various industrial sectors [23]. Table 1 briefly describes IIoT technology trends and their applications. Lack of talent in emerging digital technologies lead to a challenge in implementing IIoT solutions across industrial sectors. For example, the lack of AI knowledge and experience leads to a challenge in implementing AI solutions in manufacturing (Pokorni *et al.*, 2020).

B. LEARNING MOTIVATION THEORIES

Learning motivation is the most critical factor among the psychological characteristics that induce learners' learning activities [24]. There are internal and external conditions for the learners to prepare or participate in learning sessions. Learning motivation is an internal state or process that generates individual learning behaviors. It determines the direction and intensity of behaviors [25]. Contemporary learning motivation theories acknowledge that human cognition and individual interaction with socio-environment context are the key controls of learning motivation [26]. In expectance-value theory, motivation to learn is a function of perceived usefulness (value) and the degree to which the individual will be successful (expectance). Attribution theory is extended from the expectance-value theory to explain the why of the antecedents of expectance and value. Humans tend to establish a cause-effect relationship for events like learning a skill, which they try to attribute to a reason. If the result is positive, then the learner is content. When the result is negative, they attribute it to environmental characteristics (like social norms, social influence) or personal characteristics (like health, mood). In SCT (social cognitive theory) [27], self-efficacy, or the people's belief about their capabilities, results in successful learning and goal achievement. As per self-determination theory [28], actions can be due to intrinsic or extrinsic motivation. Curiosity is intrinsic, while earning a reward or avoiding anxiety is extrinsic.

Intrinsic motivation is essential, but most activities by people are extrinsically motivated. Goal-orientation theory [29] focuses on the why and how of the learning. Learners tend to have performance goals from a fixed growth mindset like mastering content or doing better than others or avoiding failure. ARCS (attention, relevance, confidence, satisfaction) is a four-step model [30] that covers the learning process's motivators.

C. AMBIDEXTROUS BEHAVIOR

Exploitation involves extending existing skills, knowledge, and technology; exploration involves acquiring new skills, knowledge, and technologies. In the context of learning, ambidextrous behavior involves exploitation, exploration, and pursuing both simultaneously [13]. In the last couple of decades, focus on ambidextrous organization strategy [31], ambidextrous managers [32], and ambidextrous leaders [33] has drawn extensive interest among researchers. Prior studies have discussed how the role of quality management [34] and human resource management [35] enable ambidextrous learning behavior in professionals. Empirical studies of past research indicate that a higher level of exploration and exploitation at the individual level leads to a higher level of innovative performance [36] and impacts individual, group, and firm performance [16].

Individual ambidexterity [15] involve exploring new product ideas, processes, business models, skills, and technologies [13]. Self-efficacy and leadership are identified as

TABLE 1. **IIoT and emerging digital technologies.**

Technology	What is it?	Industrial IoT use case	Reference
IoT	Cost-effective sensors and networks for real-time data gathering to monitor and make decisions	Use of IIoT to implement a smart assembly line of the smart factory. Integrate sensor networks and control systems improve productivity and safety	[23]
AR/VR	An interface that converts information about the real world in an immersive, contextual, and interactive manner to the user	Onsite and remote workers can make a better decision in an IoT enabled smart factory setup using AR/VR based live manual. Safety training in a refinery by simulating emergencies like a pipe leak	[24]
AI/ML	Tasks are performed by intelligent learning software systems, deriving inputs from the environment	ML techniques for predictive maintenance, process, and supply chain optimization. Cost reduction by reducing testing time & warranty cost, improvement in yield and quality	[25]
Robotics	Transformation of industries by automating tasks with robots having skills and intelligence	Automate tasks like material handling, perform invasive operations	[26]
Big data and analytics	Computational tools are used for developing insights for decision-making through visualization. They use the information hidden in large volumes of unstructured data of variety and velocity.	Adopting IoT in manufacturing (tools, plants, equipment, vehicles) sensory systems leads to an increase in industrial big data. Analytics on the collected data from products and processes to solve critical problems like the root cause of faulty or low-quality product	[27]
Blockchain	Implements a public ledger using a distributed database and to keep records of all transactions among a set of participating entities.	Blockchain 3.0 addresses IIoT security and facilitates data collection and storage techniques need of Industry 4.0. Applications like smart contracts involve trust, security, and decentralization across industrial setups.	[28] [29]
Cybersecurity	Cybersecurity involves the cyber-attack related threats associated with the assets of an industrial setup.	A connected smart factory and industrial control system need to protect and prevent unauthorized access.	[18] [30]

the traits that predict professionals' ambidextrous learning behavior [14]. However, learning behavior towards fast-changing technologies has received little focus.

D. TECHNOLOGY ADOPTION THEORIES

It is critical to learn and adopt essential digital skills in the work environment. However, learning advanced and emerging digital capabilities is vital for professionals to develop digital solutions and stay relevant in their job [37]. Our study analyzes the factors that influence professionals' learning behavior towards emerging digital technologies to develop industrial IoT solutions. Hence, we analyzed the technology adoption theories and the constructs used in each that influence the intention to use a new system.

Information systems (IS) literature emphasizes the key factors influencing users' acceptance of a new system. The purpose of the new systems under study vary that help users' ease their day to day activities. New systems provide mechanisms to improve productivity or performance [38] or ease the learning process via learning from e-learning systems [39], [40] or YouTube [41], [42] or mobile learning systems [44], [50], [51].

Behavioral intention of using technology is explained by most commonly used technology acceptance models [46] and technology adoption theories [47]: TRA (theory of reasoned action) [48], TAM (technology acceptance model)[49], TAM2 [50], TAM3 [51], MM (motivational model), TPB (theory of planned behavior) [52], IDT (innovation diffusion theory) [53] and SCT [27]. Earlier research also shows that some of these theories are combined to predict behavioral intention and the use behavior. The Combined-TPB-TAM model combines TPB and TAM. UTAUT (unified theory of acceptance and use of technology)[54] and UTAUT2 [55] combines eight theories: TRA, TAM, TPB, MM, IDT, C-TPB-TAM, SCT, and MPCU (model of PC utilization) [56]. As per theory of task-technology-fit (TTF), if the capabilities of information technology match the task, technology is more likely to have a positive impact on individual performance [57], [58]. Over decades of study and empirical research, most of these theories have identified antecedents that predict the behavioral intention and the use behavior of technology.

Key antecedents that predict behavioral intention are perceived ease of use, usefulness, and behavioral control. Some of these antecedents are further predicted by personal and socio-environmental factors. Some of the key personal factors are attitude, image, anxiety, and personal innovativeness. Socio-environmental factors are job relevance, relative advantage, subjective norm, and facilitating condition. Focus is on various user groups like students, professionals, and general users [59]. Further, UTAUT introduced the moderation effect of age, experience, gender voluntariness on the relationship between the antecedents and the behavioral intention.

E. UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY

UTAUT [54] is used to assess the likelihood of success in introducing new technology. By understanding the drivers of acceptance, practitioners can plan interventions to increase the acceptance by the population who are not inclined to adopt the new technology. Original article [54] has been widely cited in the context of technologies like websites, mobile technologies [45], and various information systems [60].

Researchers have extensively used technology adoption theories to study learning behavior using technology like mobile learning systems [50], [51]; learning from YouTube [41], [42]. Further, previous research shows the use of UTAUT in the adoption of e-learning systems [39], [40]; and mobile learning systems [43]. Self-efficacy and leadership are identified as psychological traits and antecedents that predict professionals' ambidextrous learning behavior [14]. However, the study of learning behavior towards fast-changing emerging technologies to develop digital solutions is sparse.

III. THEORY BUILDING AND RESEARCH MODEL

For managers who need to introduce new technologies and evaluate the likelihood of their success, UTAUT [54] is a useful tool. One can identify primary factors for technology acceptance and plan interventions specific to a population that is averse to adopting and using new systems. There are two key reasons for its popularity [59]. First, it identified the antecedents of the core constructs behavioral intention and actual use behavior, and second, it introduced the moderator effect between antecedents and the behavioral intention.

Researchers have extended technology acceptance theories to study learning orientation and ambidextrous learning behavior. Self-efficacy from SCT [61] predicts professionals' ambidextrous behavior [14]. However, it does not cover all the factors that may influence professionals' learning behavior towards fast-changing emerging digital technologies to develop digital solutions. Moreover, the studies related to learning have not determined all essential factors that could play an important role in learning behavior towards fast-emerging digital technologies. Therefore, this study attempts to fill this gap by integrating UTAUT with factors triggered by the fast-changing digital technologies used to develop digital solutions for the industrial IoT environment.

Technology acceptance models are chosen to analyze the antecedents of intention to learn and the actual learning behavior towards fast-changing emerging digital technologies. Explanation below captures how they are related.

First, Technology acceptance models capture users' intention to use and use behavior of technology in various technological contexts. In our study, we intended to analyze professionals' behavior towards emerging digital technology. Professionals need the emerging digital skills to develop digital products and services for IIoT solutions. Professionals need to learn the technology before using it to develop digital solutions. For example, professionals learn emerging digital technologies like AI/ML, AR/VR, or cloud technologies to develop industrial IoT solutions. Hence, the emphasis is to study the learning behavior in terms of intention to learn and actual learning behavior of emerging digital technologies.

Second, based on the authors [62], we have found that intention to learn does not always result in actual learning behavior. Hence, we wanted to choose a theoretical model that helps analysis of both "intention" and "actual" behavior and not "just" the actual learning behavior. Since technology acceptance models address both "intention" and "actual" behavior, we have used technology acceptance models for our study.

Third, researchers [14] have established that self-efficacy and leadership influence learning orientation and individual ambidextrous behavior. However, this theory has not considered various personal and socio-environmental antecedents that impact "intention" and "actual" behavior. Ambidextrous learning behavior is extremely critical to cope with the fast-changing development in emerging digital technologies. Hence, we analyzed the personal and socio-environmental factors to understand the professional's intention to learn and actual learning behavior.

Fourth, since our study involves studying professionals' learning behavior, one option was to use learning motivation theories. Since technology acceptance theories use antecedents from learning motivation theories, it was appropriate to use the technology acceptance theories to analyze the intention and actual learning behavior.

Finally, we chose to study the intention to learn and actual learning behavior rather than intention to use and actual use behavior of the emerging digital technology. This is because, professionals learn with an intent to use the technology. Hence, analyzing "intention to learn and actual learning behavior" was more important compared to "analyzing the intention to use and use behavior of emerging digital technologies".

This study has proposed the Learning Emerging Digital Skills (LEDS) behavioral model, as shown in Fig. 1. Like the individual ambidextrous learning theory [14], learning intention and learning behavior is adapted from the UTAUT framework. Constructs from technology adoption models [63] are used as antecedents that predict the behavioral intention to learn emerging digital technology that impacts their role in the future of work. Professional's intention to learn predicts the actual learning behavior towards emerging digital technologies. Further, we have studied the constructs that result in the moderation effect on the relationship between the antecedents and the behavioral intention to learn emerging digital technologies. In summary, in the context of emerging digital technologies, the antecedents, behavioral intention to learn, and actual learning behavior produce LEDS behavioral model. Additionally, the LEDS model also includes the moderators that affect the relationship between antecedents and behavioral intention to learn.

A. LONG-TERM CONSEQUENCE

In the model of PC utilization, the long-term consequence is introduced [56]. It explains the result of working in a specific technology in terms of payoff in the future. It could be an outcome in terms of increasing opportunity, job flexibility, and a meaningful career. The motivation to adopt may arise to future-proof oneself rather than just meeting a current need. In the fast-changing digital technologies for developing industrial IoT solutions, the long-term consequence is the antecedent that predicts behavioral intention to learn. If the long-term consequence is positive, it will positively impact the behavioral intention to learn. Therefore, we state our first hypothesis.

H1: The impact of long-term consequence (LTC) on behavioral intention to learn emerging digital technology is positive.

B. ANXIETY

SCT [27] and TAM3 [51] show anxiety in using new technology is a key antecedent of behavioral intention to learn. Learning comes with two types of anxiety: ''learning anxiety'' and ''survival anxiety.'' The first is the fear that something new will be too difficult and will lead to a loss of self-esteem. The second arises from knowing that change is necessary for survival – this may lead potential learners to start learning eventually. Learning is triggered when survival anxiety exceeds learning anxiety [64]. Technology anxiety [65] is a result of technological advancements that could lead to skill obsolescence [66], professional obsolescence [8], and fear of unemployment [67].

New jobs are being created in the fast-changing digital technologies for developing industrial IoT solutions while existing jobs are getting obsolete [8], [67]. So, anxiety for survival due to technology advancements is identified as one of the antecedents that predict behavioral intention to learn. The higher the anxiety, the higher would be the behavioral intention to learn. Hence, we state the second hypothesis.

H2: The impact of anxiety (ANX) on behavioral intention to learn emerging digital technology is positive.

C. SOCIAL INFLUENCE

The intention is expected to be directly affected by social influence [54]. The perception that family, friends, and peers believe they should learn emerging digital technologies define social influence. Social influence is one of the antecedents that predict behavioral intention to learn emerging digital technologies. If the social influence to learn a technology is high, it will positively impact the behavioral intention to learn. Consequently, we state the third hypothesis.

H3: Social influence (SI) positively impacts behavioral intention to learn emerging digital technologies.

D. JOB RELEVANCE

Employees are motivated to learn when they can see that the learned skill helps them pursue their aspirations and goals. The extent of an individual's conviction that the emerging digital technology would be helping to follow their career aspiration defines relevance. Applicability of the technology to the job is also defined as job relevance in TAM2 [50]. In the fast-changing digital technologies for developing industrial IoT solutions, the job relevance related to a technology predicts behavioral intention to learn. If the technology's job relevance is positive, it will positively impact the behavioral intention to learn. So, we formulate the fourth hypothesis.

H4: The impact of job relevance (REL) on behavioral intention to learn emerging digital technology is positive.

E. PERSONAL INNOVATIVENESS

Highly innovative individuals search for information actively regarding new concepts. Such individuals can cope with uncertainties involved with new ideas and optimists in accepting them. Personal innovativeness is the inclination towards exploring new technology. This variable is introduced in the modified TAM model [68], which suggests that personal innovativeness affects intention and actual behavior. The innovativeness of professionals predicts behavioral intention to learn emerging digital technologies. If the professional's innovativeness is high, it will positively impact the behavioral intention to learn. So, we formulate the fifth hypothesis:

H5: The impact of personal innovativeness (PIN) on behavioral intention to learn emerging digital technology is positive.

F. BEHAVIORAL INTENTION TO LEARN AND ACTUAL LEARNING BEHAVIOR

Behavioral intention is one of the key predictors of actual behavior [52], [54], [55]. We use behavioral intention to learn (BIL) and actual learning behavior (ALB) to measure the intention to learn and actual learning behavior of emerging digital technology. Accordingly, we propose that professionals' actual learning behavior could be predicted by their willingness to learn emerging digital technologies. Therefore, we state the sixth hypothesis.

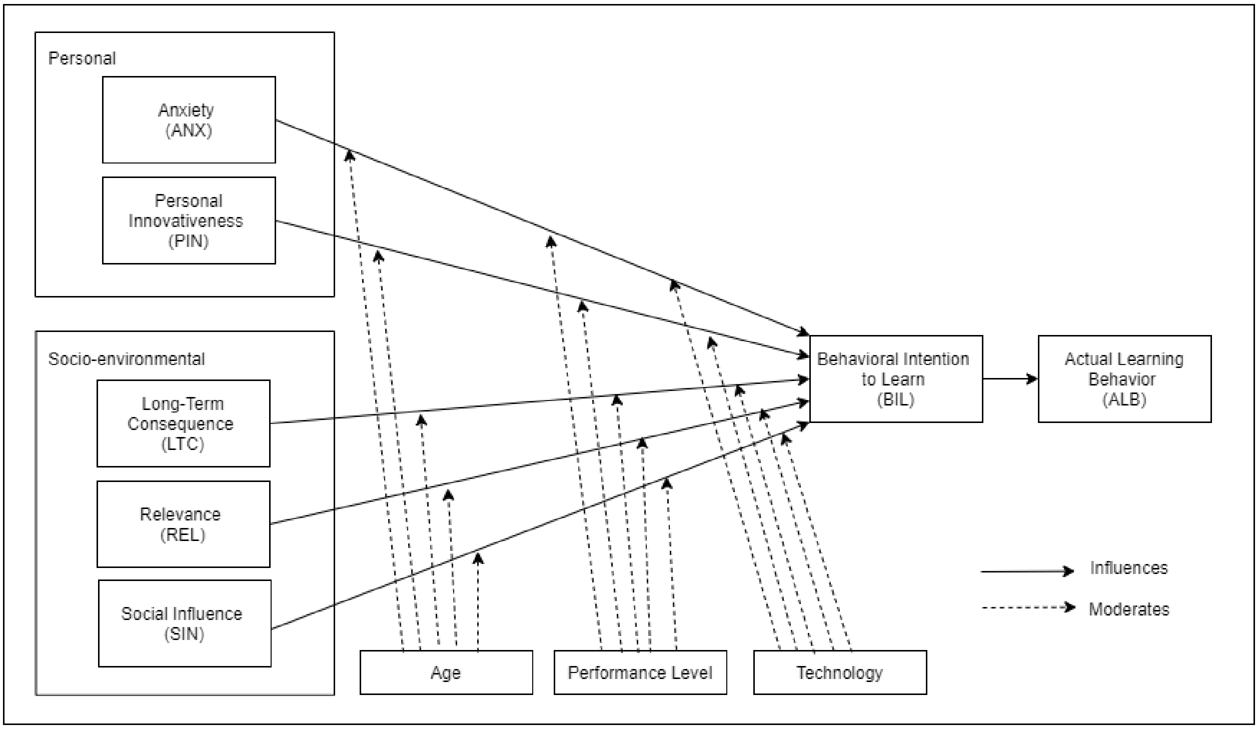

FIGURE 1. **Learning of emerging digital skills (LEDS) behavior model showing professionals behavior in learning emerging digital technologies.**

H6: Behavioral intention to learn (BIL) emerging digital technologies positively impact actual learning behavior (ALB).

G. MODERATORS

Professional's gender (male or female) influences the prediction pattern on learning intention towards emerging digital technologies.

Companies following a bell curve technique use the performance rating scale to rate each employee's performance level. A typical bell curve contains five ratings - exceptional performance, exceeds expectation, meets expectation, improvement needed, and unsatisfactory. Professionals' performance rating plays a considerable role in learning and influencing the relationship between the antecedents and the behavioral intention to learn.

Further, depending on the maturity and potential usage of technology, professionals' behavioral intention to learn the technology could differ. As per the "association for computing machinery computing classification system (ACM CCS)", technology maturity is influenced by the maturity of computing methods, networking capabilities, information systems, and functionality related to security and privacy. The key digital technologies in IIoT that could influence the behavioral intention are IoT, AI/ML, big data analytics, AR/VR, robotics, and cybersecurity.

Based on the above three moderating variables, we formulate the below three hypotheses.

H7a: Professional's gender impacts the pattern of prediction of behavioral intention to learn.

H7b: Professional's performance level impacts the pattern of prediction of behavioral intention to learn.

H7c: The technology of interest that the professionals aspire to learn impacts the pattern of prediction of behavioral intention to learn.

H. LEDS BEHAVIORAL MODEL

The hypotheses H1 to H7, drawn up within this study, are represented as the Learning of Emerging Digital Skills (LEDS) behavior model, as in Fig. 1.

LEDS model contains the dependent constructs - behavioral intention to learn and learning behavior, which are derived from UTAUT [54]. In the context of IIoT and the future of work, antecedents of the behavioral intention to learn emerging digital technologies include personal and socio-environmental factors. Personal factor personal innovativeness is derived from modified TAM [68], and anxiety from TAM3 [51], and social cognitive theory [27]. Socio-environmental factor long-term consequence is derived from MPCU [56], job relevance from TAM2 [50], and social influence from UTAUT [54]. Moderator age is used from UTAUT [54]. Further, we have introduced two additional moderators that affect the relationship between the antecedents and the behavioral intention to learn. One is the professional's performance level. The other is the technology of interest, which moderates the relationship between antecedents and behavioral intention to learn.

IV. RESEARCH METHODOLOGY

We have performed a quantitative analysis followed by a qualitative study to validate the quantitative analysis findings. This section explains the survey instrument, the data sampling strategy, and respondents' profiles.

A. SURVEY INSTRUMENT

For validating the proposed LEDS model, a questionnaire was developed for the survey. The questionnaire was prepared to collect responses across two dependent variables: behavioral intention to learn, learning behavior; five independent variables: long-term consequence, personal innovativeness; job relevance; anxiety; and three control variables to check moderation effect: age, performance rating, and technology of interest.

The constructs intention to learn, learning behavior, and social influence derive items from UTAUT [54], long-term consequence from MPCU [56], personal innovativeness from modified TAM [68]; job relevance from TAM2 [50], and ARCS motivation theory [30], anxiety from TAM3 [51] and social cognitive theory [27]. To fit the items into the context of the current study, minor changes were made. Table 13 in APPENDIX covers the details of each item.

The literature review was the basis of identifying these variables, followed by expert reviews and the pilot survey. Expert review was done with 30 experts, followed by a pilot survey with 55 experienced professionals from selected companies. Few constructs and items were dropped, and few were refined based on the expert inputs. Further, based on the pilot phase, reliability was enhanced based on Cronbach's α, as shown in Table 7. We arrived at 39 questions across five sections for the full-scale survey.

The questionnaire was designed to have five sections. Sections 1 and 2 had 19 questions about the respondent's demographic and employer information. Section 3 consisted of questions on respondent's interest and competency level across various emerging digital technologies of IIoT like IoT, AI/ML, big data, blockchain, AR/VR, robotics, and cybersecurity. Sections 4 and 5 consisted of 20 items related to 7 constructs. Within each construct, items were grouped to ensure that the respondents followed a logical flow. Such a grouping format is recommended for predicting user behavior [69].

The personal variables included in the analysis were gender [70], performance level [71], and the respondent's technology preference to learn. All control variables were converted into dummy nominal variables. To see any difference in the learning behavior related to various technologies, technology preference to learn is captured as a control variable among the technologies like IoT, AI/ML, big data, blockchain, AR/VR, robotics, and cybersecurity.

B. DATA COLLECTION

Data sampling strategy and profile of respondents is captured in this section.

1) SAMPLING STRATEGY

We performed a national level survey among professionals who worked in India's engineering R&D services firms and engaged in designing and developing IIoT products and solutions. The respondents work on IIoT projects across industry sectors like telecommunication, industrial, automotive, aerospace, energy & utilities, healthcare, consumer devices, home & building automation, and oil & gas. The sampling method was random across the north, south, eastern, and western zones of India. The list of organizations approached for initiating this survey was based on their listing in NASSCOM (National Association of Software and Service Companies), India.

A formal letter of authorization was shared with the participating organizations to allow the employees to participate and respond to the survey, ensuring anonymity. Data were collected from 95 firms in India on print copies and were entered into a database for further analysis. Data collection happened from June 2019 to Mar 2020. 55% response rate was achieved, with 685 responses, which is in line with the preferred sample size of 1:4 to 1:10, based on the number of items [72]. "A five-point Likert scale with values ranging from 'strongly disagree' to 'strongly agree' " was used to measure all the items under each construct. Positive coding was used for most of the items.

The demography of self-reported collected data is validated from the digital source [73] like the respondents' LinkedIn profile in a non-intrusive manner. Further, from the 95 participating organizations, the participating employees' data within the internal systems were used for performance indicators and actual learning of courses undertaken in specific technologies. Thus, this study combines self-reported surveys as well as internal enterprise systems data for the final analysis.

2) PROFILE OF RESPONDENTS

Respondents were chosen from companies engaged in developing IIoT products and solutions using emerging digital technology. Respondents were chosen from various large, medium, small, and micro size companies like TCS, Tech Mahindra, Infosys, Happiest Minds, Altran, Oracle, Siemens, Tejas Networks, Ericsson, GE, LGE, Keysight across 14 locations spanning across north, east, south, and west zone of India. Most of the respondents work on IIoT projects across industry sectors like telecommunication, industrial, automotive, aerospace, energy & utilities, healthcare, consumer devices, home & building automation, and oil & gas. Out of 685 datasets, 669 datasets were considered after removing outliers, as discussed in the structural equation modeling analysis section. Table 2 presents the demographic information of 669 respondents.

97% of the respondents fall in the age group of 24 to 53 years. Only 2% of the respondents were less than the age of 23 and 1% above the age of 53. The gender ratio of the respondents was 82% male and 18% female.

V. ANALYSIS AND FINDINGS

A. NORMALITY

For each variable, normality was tested using the approach of skewness-kurtosis [74]. Data is considered normal when skewness and kurtosis fall within their acceptable limits

TABLE 2. Respondents demographic and other related information.

Variable	Description	Frequency	Frequency %
Gender	Male	548	82%
	Female	121	18%
Age Group (years)	≤ 23	15	2.2%
	24 to 28	213	31.8%
	29 to 38	354	52.9%
	39 to 53	83	12.4%
	> 53	4	0.6%
Work experience (years)	< 2	61	9.1%
	2 to 5	215	32.1%
	5 to 10	224	33.5%
	10 to 15	113	16.9%
	15 to 20	43	6.4%
	20 to 25	11	1.6%
	> 25	2	0.3%
Performance rate (in the bell curve)	Exceptional performance	132	19.7%
	Exceeds expectation	100	14.9%
	Meets expectation	327	48.9%
	Improvement needed	53	7.9%
	Unsatisfactory performance	5	0.7%
	Prefer not to say	52	7.8%
Zone	East (Bhubaneswar, Kolkata)	71	11%
	West (Mumbai, Pune)	208	31%
	North (National Capital Region, Chandigarh, Lucknow)	81	12%
	South (Bengaluru, Chennai, Hyderabad, Kochi)	309	46%
Organization size (Headcount)	Large (≥250)	355	53.1%
	Medium (50-249)	137	20.5%
	Small (10-49)	117	17.5%
	Micro (<10)	55	8.2%
	Self-employed (0)	5	0.7%

(-2 to $+2$ for skewness, -7 to $+7$ for kurtosis). Using AMOS 20.0, we found that skewness and kurtosis were within corresponding limits, as shown in Table 3.

Mahalanobis d-squared is "distributed as a central chi-square statistic with degrees of freedom equal to the number of variables" [75], [76]. Typically for a multivariate outlier, the value of Mahalanobis d-squared is significantly different from other data points. Table 14 in APPENDIX shows some outliers having significant (p1 <0.05) records with Mahalanobis d-squared value. These records are removed from the data set before doing the analysis.

B. STRUCTURAL EQUATION MODELING ANALYSIS

Data collected from the survey is analyzed using the structural equation model (SEM) technique was used. Further, we used SEM to validate the hypotheses and validate the LEDS conceptual model. This versatile statistical modeling tool was used in two stages (i) evaluation of the measurement model, (ii) estimation of the structural model.

TABLE 3. Assessment of data quality.

Constructs	Items	Mean	Std deviation	Skewness	Kurtosis
SI	SI3	3.82	0.845	-1.494	2.464
	SI2	3.90	0.677	-1.847	5.429
	SI1	3.91	0.727	-1.278	3.035
REL	REL3	4.10	0.750	-1.197	2.317
	REL2	4.13	0.742	-1.252	3.012
	REL1	4.09	0.743	-1.386	3.739
LTC	LTC1	4.22	0.778	-1.256	2.764
	LTC2	4.28	0.782	-1.337	3.178
	LTC3	4.29	0.769	-1.358	3.177
	LTC4	4.23	0.791	-1.250	2.830
PIN	PIN3	3.99	0.654	-1.543	5.790
	PIN2	4.10	0.572	-1.837	6.058
	PIN1	4.19	0.601	-1.317	6.234
ANX	ANX1	4.10	0.750	-1.629	4.868
	ANX2	4.13	0.742	-1.513	4.293
	ANX3	4.09	0.743	-1.535	4.340
BIL	BIL2	3.70	0.787	-1.173	1.215
	BIL1	3.60	0.784	-.987	.798
ALB	ALB2	4.16	0.638	-1.415	5.542
	ALB1	4.17	0.675	-1.706	6.661

TABLE 4. Results of measurement model.

CFA fit indices	Threshold value	Results of measurement model	
		Initial model	Modified model
CMIN/DF	≤ 3.000	2.795	2.571
GFI	≥ 0.90	0.944	0.946
AGFI	≥ 0.80	0.921	0.924
NFI	≥ 0.90	0.963	0.964
CFI	≥ 0.90	0.976	0.977
RMSEA	≤ 0.08	0.051	0.048

1) EVALUATION OF MEASUREMENT MODEL

For evaluating the measurement model, confirmatory factor analysis (CFA) was performed to assess model fitness, construct validity test, and construct reliability test.

a: MODEL FITNESS

Table 4 shows the value of CFA fit indices from the initial measurement model of 685 datasets and a modified measurement model of 669 datasets after removing outliers based on the Mahalanobis d-squared values captured in Table 14 in APPENDIX.

b: VALIDITY TEST

As part of the validity test, we conducted content, convergent, and discriminant tests.

Content validity test is done to inspect if the items describe the context of the construct. We ensured content validity through literature review and expert opinion. Construct validity test is a two-step process, which involves the inspection of convergent and discriminant validity. Convergent validity examines if the item of a construct is less correlated with the item of another construct compared to the correlation with one another within the same construct [77]. For convergent validity, composite reliability (CR) is expected to be higher than 0.70. AVE should be greater than 0.50, and CR should be higher than AVE [78]. Table 5 shows that CR is more than 0.7, AVE is more than 0.5, and CR is more than AVE for all constructs. This result demonstrates convergent validity.

TABLE 5. Convergent validity related statistics.

Constructs	AVE	CR
LTC	0.773	0.931
ANX	0.789	0.918
SI	0.589	0.809
REL	0.748	0.899
PIN	0.748	0.899
BIL	0.790	0.882
ALB	0.891	0.942

The discriminant validity test verifies that the items of one construct with convergent validity are not significantly correlated with items of any other construct [79]. Table 6 shows that all constructs have AVE > MSV and AVE > ASV, demonstrating discriminant validity.

TABLE 6. Discriminant validity related statistics.

Constructs	AVE	MSV (AVE > MSV)	ASV (AVE > ASV)
LTC	0.773	0.038	0.021
ANX	0.789	0.035	0.024
SI	0.589	0.013	0.034
REL	0.748	0.029	0.025
PIN	0.748	0.038	0.021

c: RELIABILITY TEST

For an acceptable level of scale reliability of all constructs, Cronbach's α is expected to be higher than 0.70 (Nunnally, 1978), and composite reliability (CR) should be below 0.70. The average variance extracted (AVE) should be greater than 0.50 [74]. As captured in Table 7, for all latent constructs, statistical results showed that the value of Cronbach's α is above 0.70. Further, CR for all latent constructs was below 0.70. Similarly, AVE's value is above 0.50, which is recommended for all latent constructs [74]. This result indicates that the reliability of the constructs is adequate.

d: COMMON METHOD BIAS

The survey was designed by placing items of dependent variables to follow the items of independent variables and not the vice-versa to avoid common method bias. Additionally, it was verified that the correlation coefficient between constructs is not very high and within 0.60. Overall, it demonstrates that common method bias is not observed. Similarly, socially desirable response or response bias is checked and was found to be within acceptable limits.

TABLE 7. Constructs reliability.

Latent Construct	Cronbach's alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
BIL	0.882	0.882	0.790
ALB	0.939	0.942	0.891
ANX	0.918	0.918	0.789
PIN	0.894	0.899	0.748
LTC	0.934	0.931	0.773
SI	0.787	0.809	0.589
REL	0.895	0.899	0.748

2) ESTIMATION OF THE STRUCTURAL MODEL

In this stage of the structural equation model, the LEDS model's fitness was tested. The research hypotheses were validated using path analysis.

a: HYPOTHESES TEST RESULT

The structural model's goodness of fit is established by inspecting the model fit indices. It is found that Chi-square is significant (Chi-square = 443.018, DF = 153, P = 0.000). CMIN/DF value is 2.896, which is less than 3.0. Results of the fitness indices (GFI = 0.938, AGFI = 0.915, NFI = 0.963, RFI = 0.954, IFI = 0.975, TLI = 0.969, CFI = 0.975, RMSEA = 0.053), indicate that the goodness of fit of the structural model with the observed data is adequate [74].

The research hypotheses were tested by performing path coefficient analysis. Table 8 captures the standardized regression weights.

TABLE 8. Results of hypotheses testing.

Hypothesized path	Estimate	p-value	Result
BIL <-- ANX	.117	***	Verified
BIL <-- PIN	.271	***	Verified
BIL <-- LTC	.145	***	Verified
BIL <-- REL	.186	***	Verified
BIL <-- SI	.347	***	Verified
ALB<-- BIL	.598	***	Verified

Note: *** implies p < 0.001

b: Sample ComparisonS (Gender)

Multiple group analysis was performed to verify if gender impacts the intention to learn. As seen in Table 9, the model result shows that the impact of predictors of intention to learn is slightly different across female and male respondents.

c: SAMPLE COMPARISONS (Performance Rating)

Multiple group analysis was conducted in the model result to compare the behavior based on the employee's performance

TABLE 9. Comparison of the path coefficient results between male and female.

Hypothesized path	Gender (Male)		Gender (Female)	
	Estimates	p-value	Estimates	p-value
BIL <-- ANX	0.112	0.001	0.194	0.022
BIL <-- PIN	0.28	***	0.248	***
BIL <-- LTC	0.118	0.001	0.19	0.03
BIL <-- REL	0.162	***	0.206	0.012
BIL <-- SI	0.406	***	0.156	0.035
ALB <-- BIL	0.552	***	0.733	***

TABLE 10. Comparison of the path coefficient results across performance ratings.

Path	Meets expectation		Exceeds expectation		Exceptional performer	
	Est.	p	Est.	p	Est.	p
BIL<-- ANX	0.170	***	-	0.337	-	0.311
BIL<-- PIN	0.108	0.045	0.478	***	0.514	***
BIL<-- LTC	0.110	0.002	-	0.890	-	0.607
BIL<-- REL	0.262	***	-	0.124	-	0.932
BIL<-- SI	0.518	***	0.238	0.001	-	0.499
ALB<-- BIL	0.642	***	0.653	***	0.617	***

rating. As shown in Table 10, it shows that the respondent's performance rating moderates the predictor's impact on the intention to learn. Behavior is analyzed across three classifications: meets expectation, exceeds expectation, and exceptional performance. For exceptional performers and performers with exceeding performance levels, personal innovativeness is the only predictor of behavioral intention to learn. Whereas, for average performers (tagged as meets expectation), anxiety, relevance, and social influence are significant predictors of behavioral intention to learn.

d: SAMPLE COMPARISONS (TECHNOLOGY-WISE ASPIRATION TO Learn)

Multiple group analysis was conducted to compare the aspiration to learn across various emerging digital technologies. As seen in Table 11, the test shows the difference in predictors' impact on learning intention across different technologies.

Social influence is a relatively strong factor with a regression weight of 0.419 and 0.375 in learning intention towards AI/ML and big data related technologies compared to other technologies. Job relevance is significant (p-value < 0.05) across all technologies except in blockchain (p-value > 0.05). Minor differences were observed related to the impact of anxiety, personal innovativeness, and long-term consequence on the intention to learn across all technologies.

C. QUALITATIVE STUDY

Findings from the SEM analysis is validated through a qualitative study [80]. This step of the study was performed to understand the reason and mindset behind the survey responses. Also, the qualitative phase helped to comprehend the quantitative results in greater depth and validate the findings.

1) QUALITATIVE RESEARCH METHOD

We have used the phenomenology approach [81], which is used to explore human experience in a phenomenon [82]. The phenomenon could be an object, event, or experience. In the current study, we wanted to understand the organizational leadership experience concerning employees' behavior towards learning emerging digital technologies. We chose the phenomenon method over grounded theory since we intended to validate the findings from the quantitative study from the experience of experts [83]. In contrast, grounded theory identifies themes from qualitative data and develops a new theory or hypotheses from scratch [82], hence was not used.

2) DATA COLLECTION

For the data collection, an in-depth semi-structured interview was conducted with 30 executives, including the C-level executives and senior leaders across 20 organizations. Out of the 95 organizations that were probed for survey during the quantitative research phase, 20 organizations were selected with equal coverage on size and location. The phenomenological research approach involves methodical reflection on the lived experience of changing systems [84]. Hence, participants were selected if they had the experience [82] of managing talent development in the fast-changing environment of emerging digital technologies. Interview requests were sent to 40 senior executives, out of which 30 accepted the invite. Interviews were conducted with these 30 participants over four months from July to October 2020. One-o-one interviews were scheduled and conducted for 30 to 45 minutes. Some of the respondents were interviewed multiple times to avoid wrong interpretation and bias. Notes from the interviews were entered and managed using Microsoft Excel software. While responding to questions, interviewees also referred to their organization strategy, reports from capacity planning, resource management, talent acquisition, learning & development and human resource development functions.

Below are the four sets of guiding questions and few sample responses from the semi-structured interview. The first one is a generic question, followed by questions specific to our study.

Q1: To stay competitive and cope with the changing technological environment, what practices does the organization follow to stay ambidextrous? What strategy do you follow to stay competitive in the marketplace? What practices do you follow to meet the talent demand? What kind of learning and development practices does the organization follow to meet the talent demand in emerging digital technologies? *Reply: Community of Practices is a standard method used for emerging technology-related skill development programs by learning & development (L&D) function throughout the year.*

TABLE 11. Comparison of the path coefficient results among technologies.

Path	IoT		AI/ML		Big Data		Blockchain		AR/VR		Robotics		Cybersecurity	
	Est.	p	Est.	p	Est.	p	Est.	p	Est.	p	Est.	P	Est.	p
BIL<-ANX	0.135	0.007	0.089	0.046	0.201	***	0.231	***	0.158	***	0.105	0.013	0.101	0.021
BIL<-PIN	0.226	***	0.234	***	0.172	***	0.165	0.008	0.173	0.009	0.193	***	0.203	***
BIL<-LTC	0.212	0.001	0.141	***	0.192	***	0.262	***	0.364	***	0.356	***	0.351	***
BIL<-REL	0.251	***	0.197	***	0.141	0.011	0.104	0.083	0.148	0.003	0.141	0.013	0.127	0.019
BIL<-SI	0.232	***	0.419	***	0.375	***	0.281	***	0.231	***	0.247	0.001	0.253	***
ALB<-BIL	0.563	***	0.528	***	0.582	***	0.583	***	0.505	***	0.553	***	0.574	***

Q2: What makes the employees nominate to the skill development programs to reskill or upskill in emerging digital technologies? What makes them learn new skills? What are the personal traits and environmental influencing factors? *Reply: Alignment between the organizational goal and employee aspiration is a common practice. While discussing the career path, managers encourage their subordinates to continuously reskill and upskill to stay relevant and faster career growth.*

Q3: Once self-nominated, do they complete the skill development programs or drop out? What are the reasons for dropping out? *Reply: They must complete the program to get the course completion certificate. Sometimes they drop out due to the challenge in balancing with the bandwidth demand from ongoing projects. Not everyone is ready to stretch to balance project delivery and upskilling.*

Q4: What are the other factors that moderate their learning behavior? What makes employees chose to learn one technology over the other? *Reply: They are ready to invest time in learning a new skill when there is a visibility of doing a project in the near future. For example, since the number of cloud technology projects is high, they may like to learn cloud technologies rather than blockchain. High performers are self-driven and have a higher level of learning aptitude and vice-a-versa.*

3) DATA ANALYSIS

Responses from all the interviews were transcribed verbatim, followed by thematic analysis. After multiple rounds of analysis of the transcriptions, we categorized them into themes. Responses from question two were categorized under various antecedents that influence behavioral intention to learn. Responses from question three and four were categorized under the moderators that affect the relationship between the antecedents and the behavioral intention to learn.

4) FINDINGS FROM QUALITATIVE STUDY

The responses were categorized under themes job relevance, anxiety, innovativeness, social influence, and long-term impact, which influence the learning behavior. Table 12 captures some of the unique responses and their mapping to various themes.

TABLE 12. Themes from interview responses.

Response	Theme
• New skill is relevant to the current job. • Role demands upskilling to stay updated in the emerging skills • Industry trends on future of job • New project demands competency development of 4 to 6 weeks	Job relevance
• Skills in internal job posting leads to threat of job loss and create anxiety • Stress builds up towards end of current project. Then they discuss about opportunities and prepare accordingly • Anxiety and uncertainties about the future assignments' trigger upskilling	Anxiety
• Passion to experiment with new technologies • Self-driven and curiosity to learn • Develop proof-of-concepts • Active participation in organization-wide Hackathons	Personal innovativeness
• Encouraged by managers to reskill. Managers do training need analysis and recommend • Influenced by friends and peers • Encouragement and inspiration from seniors • Managers encourage teams to reskill based on skills in demand • Quarterly leadership meetings show the technology trends and roadmap in the organization	Social influence
• Impact of the new skill in the long-term career goals • Long term career aspiration • Change in career plan	Long-term consequence

Similarly, on the moderation effect, responses are categorized under gender, performance level and technology preference as explained below.

- Professional's gender has a minor moderating effect on the learning behavior. However, it is often observed that intention to learn and actual learning behavior is robust than their male colleagues. Employees from all genders realize that reskilling is key for their career growth.

However, in the pursuit to balance work-life, female employees tend to choose a skill development program that they can complete and eventually reskill themselves.

- Extraordinary performers are self-driven. Their curiosity and innovativeness drive them to learn new technologies and related skills. They are self-driven and do better time management to balance current assignments and learning new skills. However, average performers are driven by their managers and mentors to register in a skill development program. Also, many times threat of job loss due to possible skill obsolescence creates anxiety, and they go for reskilling.
- Professionals have a preference to learn a particular technology over others. Based on their perception and maturity, and the potential of using the technology in the near future, professionals chose technology to learn. Many times, they also assess how different the new technology from the current skills they possess. They prefer to go for a technology where skill distance is low. For example, someone with expertise in web application development prefers to learn cloud services and related technologies rather than learning blockchain.

VI. DISCUSSION

This section contains the key findings from the quantitative and qualitative analysis, theoretical and practical implications, limitations, and future scope.

A. KEY FINDINGS

As per the statistical analysis, it is found that construct reliability, validity, and model fitness of the measurement model were successfully achieved. Further, based on the structural model being examined, an acceptable level of predictability is obtained for the endogenous factors: behavioral intention to learn and actual learning behavior.

Social influence and personal innovativeness are the most influential factors predicting intention to learn with a regression weight of 0.347 and 0.271, respectively. Relevance, long-term consequence, and anxiety are also detected as predictors of intention to learn, measuring regression weights of 0.186, 0.145, and 0.117, respectively. Finally, a significant link was found between intention to learn and actual learning behavior, measuring a regression weight of 0.598.

Moderation effects of gender, the performance rating of professionals, and technology of interest are found on the relationship between antecedents and behavioral intention to learn. A significant difference between male and female professionals is observed in how the intention to learn predicts actual learning behavior with a regression weight of 0.552 in males, whereas it is 0.733 in females.

Further, significant differences were observed in the way predictors impact intention to learn and the actual learning behavior for employees across different performance levels. As the employee's performance improves, the intention to learn is predicted by a lesser number of factors. For exceptional performers and exceeding performance cases, personal innovativeness is the key driver of intention to learn with a regression weight of 0.514 and 0.478, respectively. Whereas, for average performers, social influence, job relevance, and anxiety are key driving factors of intention to learn with regression weights 0.518, 0.262, and 0.170, respectively. However, regression weight between intention to learn and actual learning behavior is similar across exceptional performers, exceeds expectation, and meets expectation with regression weights 0.617, 0.653, and 0.642, respectively.

Moreover, we have found that the technology itself is a moderating factor in learning behavior, which indicates the maturity of the technology in the industry. Social influence is a relatively strong factor with a regression weight of 0.419 and 0.375 in learning intention towards AI/ML and big data related technologies compared to other technologies. Job relevance is significant (p-value < 0.05) across all technologies except in blockchain (p-value > 0.05). Minor differences were observed related to the impact of anxiety, personal innovativeness, and long-term consequence on the intention to learn across all technologies.

In line with the quantitative analysis, the qualitative study found the themes related to the antecedents of behavioral intention and moderators that impact the relationship between antecedents and the intention to learn.

B. THEORETICAL IMPLICATIONS

This study explores the predictors of individuals' learning behavior in the fast-changing environment of emerging digital technologies. These technologies are crucial for developing IIoT products and solutions. We have established the LEDS model, which helps to study emerging digital technology professionals' learning behavior, establishes the hypotheses, and answers the research questions. Here are the key contributions to theory.

First, the LEDS model extends the individual's ambidextrous learning model [14] to explain the learning intention of professionals aspiring to develop IIoT solutions using emerging digital technologies. LEDS model inherits antecedents from technology adoption theories. Moreover, it empirically established that social influence, innovativeness, relevance, long-term consequence, and anxiety predict professionals' learning intention. Also, a strong relationship was found between intention to learn and learning behavior in this context.

Second, these findings are aligned with technology acceptance theories applied in analyzing the learning intention and actual learning behavior of professionals towards emerging digital technologies. Social influence is detected as a strong predictor of learning intention, which is in line with UTAUT [54], followed by personal innovativeness as per modified TAM [68]. Further, other predictors are job relevance as in TAM2 [50], long-term consequence as in MPCU [56], and anxiety as in TAM3 [51]. While social influence is one of the critical antecedents of knowledge acquisition via e-learning [85] and mobile learning [86], it is a determinant in the context of individual behavioral [87].

Our finding extends this and establishes that social influence positively impacts professionals' intention to learn emerging digital technologies. While personal innovativeness [68] has been used in the individual learning context of ICT [88], it positively impacts the behavioral intention to learn. Anxiety due to uncertainties related future of the job impacts the professional's intention to learn. This behavior aligns with anxiety behavior that affects a professional's intention and actual technology use behavior [56]. A significant linkage was observed between intention to learn and the actual learning behavior, which is in line with UTAUT [54].

Third, recent research shows individual ambidextrous learning behavior impacts individual and group performance [15], [16]. On the contrary, our study shows the moderating effect of professionals' performance on the relationship between antecedents and the intention to learn. This moderation relationship is one of the significant contributions to theory. As the employee's performance improves, the intention to learn is predicted by a lesser number of factors. For exceptional performers, personal innovativeness is the key driver in the intention to learn. Whereas, for average performers, social influence and anxiety are additional driving factors towards intention to learn.

The fourth significant contribution to theory is the moderation effect of technology on the relationship between the antecedents and behavioral intention to learn. Professionals prefer to learn a technology over the other based on technology maturity in the industry and its potential usefulness. Blockchain is expected to be a breakthrough technology. However, its comparison and significant advantage over traditional approaches are yet to be established. There is a growing realization in businesses that blockchain in industrial IoT is not mature yet.

The fifth contribution is gender moderating the relationship between antecedents and intention to learn emerging digital technologies. This behavior aligns with the moderator effect of gender on the intent and actual behavior [89], [90]. However, an additional theoretical contribution is that the strength of the relationship between intention to learn and actual learning behavior is high in female employees than male employees.

Finally, such empirical research is the first of its kind conducted in India to analyze professionals' learning behavior towards emerging digital technologies for developing IIoT solutions across industries. LEDS behavioral model is developed based on this study conducted in India.

C. PRACTICAL IMPLICATIONS

This study derives practical implications for the practitioners and decision-makers of digital transformation towards IIoT solutions and deployment. The challenge of maintaining a balance between meeting demand for emerging digital skills and executing the developmental journey of employees in the era of fast technological development can be managed by understanding the findings cited in the LEDS behavior model.

Based on the LEDS behavior model, here are some considerations for practitioners of ambidextrous organizations involved in designing ramp-up strategies to meet the current and future demand of emerging digital skills for their product and solution development programs.

- Use antecedents of employees' ambidextrous learning behavior to formulate policies to achieve ambidextrous organization's goals.
- Learning aspiration is high, with professionals having high innovativeness as they try to experiment with new technologies. Such professionals are suitable to form the core team of a project team in emerging areas.
- Employees prefer learning a particular technology by assessing its relevance to their career and the long-term consequence of learning the technology.
- Some professionals develop the anxiety of the possibility of unemployment, which may arise due to technological advancements. To stay relevant in their job, they need to reskill and upskill themselves in emerging digital technologies. One can reduce learning anxiety by creating a safer environment or increase survival anxiety by signaling career impact.
- Intention to learn as a predictor of actual learning behavior varies among male and female employees. The intention is robust in female employees and essential insight for the HR department to appropriately align HR policies.
- The social influence of peers and friends impact learning behavior. A supportive team, manager, and leadership can impact learning behavior positively.
- Perceived maturity of the technology may hamper professionals' intention to learn and the learning behavior. Hence, there is a need for extensive feasibility studies before the rollout of any reskilling program. As per our findings, the perceived immaturity level of blockchain in the industry reflects the professional's aspiration to learn blockchain technology.

These considerations can be further used as input towards policy formation to practice it widely across the organization. Organizations need to drive a learning culture by employees' aspiration to learn, rather than making an organization mandate. Organizations need to consider the factors influencing learning aspiration and employees' learning behavior as part of the learning and development strategy. A supportive learning environment in terms of institutional support and resources required to improve learning effectiveness improves diversified learning activities. If employees' perception of organizational support remains high, employees' behavior and attitude show positivity, benefiting the organization.

D. LIMITATIONS AND FUTURE RESEARCH

Theoretical and practical significance is described by identifying specific factors that are relatively more important, which affect the intention to learn and professionals' actual learning behavior. Nevertheless, there were a few limitations,

TABLE 13. Constructs and items.

Construct	Model/Reference	Items
LTC	MPCU [56]	LTC1. Learning the future skills will increase the preferred job assignment opportunities LTC2. Learning the future skills will increase the variety of job assignments LTC3. Learning the future skills will increase meaningful and relevant work opportunity LTC4. Learning the future skills will increase the flexibility of changing job
ANX	TAM3 [51] SCT [27]	ANX1. Learning of future skills does not make me feel scared ANX2. Learning of future skills does not make me nervous ANX3. Learning of future skills does not make me uncomfortable
SI	UTAUT [54]	SI1. "People who influence my behavior think that I should use the future skills." SI2. "People who are important to me think that I should use the future skills." SI3. "Using future skills is considered a status symbol among my friends."
REL	TAM2 [50] ARCS [30]	REL1. Learning the future skills is appropriate to my job REL2. Learning future skills is suitable to pursue my career aspirations REL3. Learning future skills is pertinent for my future
PIN	Modified TAM [68]	PIN1. I like to learn future skills PIN2. I like to experiment with future skills PIN3. If I hear about future skills, I look for ways to learn and experiment with it
BIL	UTAUT [54]	BIL1. I intend to learn future skills BIL2. I intend to attend training courses related to future skills
ALB	UTAUT [54]	ALB1. I am trained in the skills related to emerging technologies ALB2. I have learned the skills related to emerging technologies

which can be the scope for future research. This study was conducted only on professionals who worked in companies in India involved in the design and development of IIoT products or R&D engineering services. There is a scope to extend and analyze the LEDS model specific to the automotive, aerospace, energy, or healthcare industry. Consequently, future research should attempt to involve professionals in various other industries. Further, the impact of moderator variables like age, work experience, and salary on the intention to learn and the actual learning behavior can be analyzed.

VII. CONCLUSION

Ambidextrous learning behavior by professionals is exceptionally critical to cope with the fast-changing development in emerging digital technologies. Hence we analyzed the personal and socio-environmental factors to understand the professional's intention to learn and actual learning behavior.

TABLE 14. Mahalanobis d-squared value.

Record number	Mahalanobis d-squared	p1	p2
464	112.224	.000	.000
494	108.220	.000	.000
310	86.259	.000	.000
591	76.785	.000	.000
498	74.897	.000	.000
458	71.352	.000	.000
603	69.896	.000	.000
623	68.596	.000	.000
584	68.497	.000	.000
566	67.892	.000	.000
297	67.238	.000	.000
531	66.764	.000	.000
447	66.437	.000	.000
445	65.380	.000	.000
560	64.875	.000	.000
457	64.292	.000	.000
656	64.266	.000	.000
385	63.324	.000	.000
647	61.717	.000	.000
296	60.514	.000	.000
587	59.812	.000	.000
325	59.571	.000	.000
323	58.988	.000	.000
664	58.101	.000	.000
621	56.303	.000	.000
640	55.817	.000	.000
595	51.587	.000	.000
50	51.250	.000	.000

This empirical research is the first of its kind conducted in India to study employees' ambidextrous learning behavior in the space of IIoT and fast-changing digital technologies. In the nation-wide survey we conducted, 685 professionals working in 95 firms across sectors like industrial, energy, automotive, aerospace, healthcare, and consumer products participated. As per the LEDS model, social influence, personal innovativeness, anxiety, long-term consequence, and job relevance predict the behavioral intention to learn emerging digital technologies. Moreover, these relationships were moderated by the performance level of the professional and the technology of interest. For instance, for exceptional performers, personal innovativeness was the key driver in the intention to learn. Whereas, for average performers, social influence and anxiety are additional driving factors towards intention to learn. Understanding such behavior helps practitioners formulate the appropriate ramp-up strategy to meet the demand. Learning and development policies can be aligned to meet the current and future demand and implement the IIoT strategy.

APPENDIX

See Table 13 and 14.

REFERENCES

[1] G. Beier, S. Niehoff, T. Ziems, and B. Xue, "Sustainability aspects of a digitalized industry—A comparative study from China and Germany," *Int. J. Precis. Eng. Manuf.-Green Technol.*, vol. 4, no. 2, pp. 227–234, Apr. 2017.

[2] N. Z. N. Hasnan and Y. M. Yusoff, "Short review: Application areas of industry 4.0 technologies in food processing sector," in *Proc. IEEE SCOReD*, Bangi, Malaysia, Nov. 2018, pp. 1–6, doi: 10.1109/SCORED.2018.8711184.

[3] E. Ross, B. Schaninger, and E. S. Yue, "Right-skilling for your future workforce," McKinsey Rep., USA, Aug. 2018. [Online]. Available: https://www.mckinsey.com/business-functions/organization/our-insights/the-organization-blog/right-skilling-for-your-future-workforce

[4] O. Kovács-Ondrejkovic, R. Strack, A. Pierre, A. L. Gobernado, and E. Lyle, "Decoding global trends in upskilling and reskilling," Boston Consulting Group, Boston, MA, USA, Nov. 2019. [Online]. Available: https://www.bcg.com/publications/2019/decoding-global-trends-upskilling-reskilling.aspx

[5] J. Buvat, C. Crummenerl, M. Slatter, R. K. Puttur, L. Pasquet, and J. van As, "The digital talent gap—Are companies doing enough?" Capgemini, Paris, France, LinkedIn, Sunnyvale, CA, USA, Oct. 2017. [Online]. Available: https://www.capgemini.com/wp-content/uploads/2017/10/Digital-Talent-Gap-Report_Digital.pdf

[6] T. A. Leopold, V. S. Ratcheva, and S. Zahidi, "The future of jobs report 2018," World Econ. Forum, Geneva, Switzerland, Sep. 2018. [Online]. Available: https://www.weforum.org/reports/the-future-of-jobs-report-2018/

[7] K. Schwab and S. Zahidi, "The future of jobs 2020," World Econ. Forum, Geneva, Switzerland, Oct. 2020. [Online]. Available: http://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

[8] Y. Linyang and H. Weide, "Research on professional obsolescence: Theory retrospect, status summary and future prospects," *Foreign Econ. Manage.*, vol. 39, no. 11, Nov. 2017, Art. no. 11.

[9] T. Jacks and P. Palvia, "Measuring value dimensions of IT occupational culture: An exploratory analysis," *Inf. Technol. Manage.*, vol. 15, no. 1, pp. 19–35, Mar. 2014, doi: 10.1007/s10799-013-0170-0.

[10] G. Rong and V. Grover, "Keeping up-to-date with information technology: Testing a model of technological knowledge renewal effectiveness for IT professionals," *Inf. Manage.*, vol. 46, no. 7, pp. 376–387, Oct. 2009, doi: 10.1016/j.im.2009.07.002.

[11] M. E. Porter and J. E. Heppelmann, "How smart, connected products are transforming competition," *Harvard Bus. Rev.*, vol. 92, no. 11, pp. 64–88, 2014.

[12] A. Brem and K.-I. Voigt, "Integration of market pull and technology push in the corporate front end and innovation management—Insights from the German software industry," *Technovation*, vol. 29, no. 5, pp. 351–367, May 2009, doi: 10.1016/j.technovation.2008.06.003.

[13] J. G. March, "Exploration and exploitation in organizational learning," *Org. Sci.*, vol. 2, no. 1, pp. 71–87, Feb. 1991, doi: 10.1287/orsc.2.1.71.

[14] O.-P. Kauppila and M. P. Tempelaar, "The social-cognitive underpinnings of employees' ambidextrous behaviour and the supportive role of group managers' leadership," *J. Manage. Stud.*, vol. 53, no. 6, pp. 1019–1044, Sep. 2016, doi: 10.1111/joms.12192.

[15] Y. Zhang, F. Wei, and C. Van Horne, "Individual ambidexterity and antecedents in a changing context," *Int. J. Innov. Manage.*, vol. 23, no. 3, Apr. 2019, Art. no. 1950021, doi: 10.1142/S136391961950021X.

[16] B. Schnellbächer, S. Heidenreich, and A. Wald, "Antecedents and effects of individual ambidexterity—A cross-level investigation of exploration and exploitation activities at the employee level," *Eur. Manage. J.*, vol. 37, no. 4, pp. 442–454, Aug. 2019, doi: 10.1016/j.emj.2019.02.002.

[17] S. Talukder, R. Chiong, S. Dhakal, G. Sorwar, and Y. Bao, "A two-stage structural equation modeling-neural network approach for understanding and predicting the determinants of m-government service adoption," *J. Syst. Inf. Technol.*, vol. 21, no. 4, pp. 419–438, Nov. 2019, doi: 10.1108/JSIT-10-2017-0096.

[18] S. Fareri, G. Fantoni, F. Chiarello, E. Coli, and A. Binda, "Estimating industry 4.0 impact on job profiles and skills using text mining," *Comput. Ind.*, vol. 118, Jun. 2020, Art. no. 103222, doi: 10.1016/j.compind.2020.103222.

[19] R. Drath and A. Horch, "Industrie 4.0: Hit or hype? [Industry forum]," *IEEE Ind. Electron. Mag.*, vol. 8, no. 2, pp. 56–58, Jun. 2014, doi: 10.1109/mie.2014.2312079.

[20] Y. Liao, E. de Freitas Rocha Loures, and F. Deschamps, "Industrial Internet of Things: A systematic literature review and insights," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4515–4525, Dec. 2018, doi: 10.1109/JIOT.2018.2834151.

[21] M. J. Sousa and Á. Rocha, "Digital learning: Developing skills for digital transformation of organizations," *Future Gener. Comput. Syst.*, vol. 91, pp. 327–334, Feb. 2019, doi: 10.1016/j.future.2018.08.048.

[22] J. H. Kim, "A review of cyber-physical system research relevant to the emerging IT trends: Industry 4.0, IoT, big data, and cloud computing," *J. Ind. Integr. Manage.*, vol. 2, no. 3, Sep. 2017, Art. no. 1750011, doi: 10.1142/S2424862217500117.

[23] M. A. Ebrahimighahnavieh, S. Luo, and R. Chiong, "Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review," *Comput. Methods Programs Biomed.*, vol. 187, Apr. 2020, Art. no. 105242.

[24] R. J. Vallerand, L. G. Pelletier, M. R. Blais, N. M. Briere, C. Senecal, and E. F. Vallieres, "The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education," *Educ. Psychol. Meas.*, vol. 52, no. 4, pp. 1003–1017, Dec. 1992, doi: 10.1177/0013164492052004025.

[25] D. H. Schunk, *Learning Theories: An Educational Perspective*, 6th ed. London, U.K.: Pearson, 2012.

[26] D. A. Cook and A. R. Artino, "Motivation to learn: An overview of contemporary theories," *Med. Educ.*, vol. 50, no. 10, pp. 997–1014, Oct. 2016, doi: 10.1111/medu.13074.

[27] A. Bandura, "Social cognitive theory of self-regulation," *Org. Behav. Hum. Decis. Processes*, vol. 50, no. 2, pp. 248–287, 1991, doi: 10.1016/0749-5978(91)90022-l.

[28] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *Amer. Psychol.*, vol. 55, no. 1, pp. 68–78, 2000, doi: 10.1037/0003-066x.55.1.68.

[29] A. Nilsson, C. von Borgstede, and A. Biel, "Willingness to accept climate change strategies: The effect of values and norms," *J. Environ. Psychol.*, vol. 24, no. 3, pp. 267–277, Sep. 2004, doi: 10.1016/j.jenvp.2004.06.002.

[30] J. M. Keller, "Using the ARCS motivational process in computer-based instruction and distance education," *New Directions Teach. Learn.*, vol. 1999, no. 78, pp. 37–47, 1999, doi: 10.1002/tl.7804.

[31] M. Asif, "Strategic leadership and ambidextrous learning: Exploring the role of dynamic capabilities and intellectual capital," *Int. J. Qual. Service Sci.*, vol. 12, no. 1, pp. 1–14, Mar. 2020, doi: 10.1108/IJQSS-03-2019-0034.

[32] T. J. M. Mom, F. A. J. van den Bosch, and H. W. Volberda, "Understanding variation in managers' ambidexterity: Investigating direct and interaction effects of formal structural and personal coordination mechanisms," *Org. Sci.*, vol. 20, no. 4, pp. 812–828, Aug. 2009, doi: 10.1287/orsc.1090.0427.

[33] W. Hu, J. Luo, Z. Chen, and J. Zhong, "Ambidextrous leaders helping newcomers get on board: Achieving adjustment and proaction through distinct pathways," *J. Bus. Res.*, vol. 118, pp. 406–414, Sep. 2020, doi: 10.1016/j.jbusres.2020.06.064.

[34] M. Asif and H. J. de Vries, "Creating ambidexterity through quality management," *Total Qual. Manage. Bus. Excellence*, vol. 26, nos. 11–12, pp. 1226–1241, Dec. 2015, doi: 10.1080/14783363.2014.926609.

[35] I. Prieto-Pastor and V. Martin-Perez, "Does HRM generate ambidextrous employees for ambidextrous learning? The moderating role of management support," *Int. J. Hum. Resource Manage.*, vol. 26, no. 5, pp. 589–615, Mar. 2015, doi: 10.1080/09585192.2014.938682.

[36] F. Alghamdi, "Ambidextrous leadership, ambidextrous employee, and the interaction between ambidextrous leadership and employee innovative performance," *J. Innov. Entrepreneurship*, vol. 7, no. 1, pp. 1–14, Feb. 2018, doi: 10.1186/s13731-018-0081-8.

[37] M. Oberländer, A. Beinicke, and T. Bipp, "Digital competencies: A review of the literature and applications in the workplace," *Comput. Educ.*, vol. 146, Mar. 2020, Art. no. 103752, doi: 10.1016/j.compedu.2019.103752.

[38] M. M. Alamri, M. A. Almaiah, and W. M. Al-Rahmi, "Social media applications affecting students' academic performance: A model developed for sustainability in higher education," *Sustainability*, vol. 12, no. 16, p. 6471, Aug. 2020.

[39] M. El-Masri and A. Tarhini, "Factors affecting the adoption of e-learning systems in qatar and USA: Extending the unified theory of acceptance and use of technology 2 (UTAUT2)," *Educ. Technol. Res. Develop.*, vol. 65, no. 3, pp. 743–763, Jun. 2017, doi: 10.1007/s11423-016-9508-8.

[40] S. A. Salloum and K. Shaalan, "Factors affecting students' acceptance of E-learning system in higher education using UTAUT and structural equation modeling approaches," in *Proc. Int. Conf. Adv. Intell. Syst. Inform.*, Cham, Switzerland, 2019, pp. 469–480, doi: 10.1007/978-3-319-99010-1_43.

[41] N. Chintalapati and V. S. K. Daruri, "Examining the use of YouTube as a learning resource in higher education: Scale development and validation of TAM model," *Telematics Informat.*, vol. 34, no. 6, pp. 853–860, Sep. 2017, doi: 10.1016/j.tele.2016.08.008.

[42] N. Chintalapati and V. S. K. Daruri, "Examining the use of YouTube as a learning resource in higher education: Scale development and validation of TAM model," *Telematics Informat.*, vol. 34, no. 6, pp. 853–860, Sep. 2017, doi: 10.1016/j.tele.2016.08.008.
[43] M. A. Almaiah, M. M. Alamri, and W. Al-Rahmi, "Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education," *IEEE Access*, vol. 7, pp. 174673–174686, 2019.
[44] M. A. Almaiah, M. A. Jalil, and M. Man, "Extending the TAM to examine the effects of quality features on mobile learning acceptance," *J. Comput. Educ.*, vol. 3, no. 4, pp. 453–485, Dec. 2016.
[45] M. A. Almaiah, M. M. Alamri, and W. M. Al-Rahmi, "Analysis the effect of different factors on the development of mobile learning applications at different stages of usage," *IEEE Access*, vol. 8, pp. 16139–16154, 2020.
[46] I. Ajzen and M. Fishbein, "Attitude-behavior relations: A theoretical analysis and review of empirical research," *Psychol. Bull.*, vol. 84, no. 5, pp. 888–918, 1977, doi: 10.1037/0033-2909.84.5.888.
[47] H. Taherdoost, "A review of technology acceptance and adoption models and theories," *Procedia Manuf.*, vol. 22, pp. 960–967, Jan. 2018, doi: 10.1016/j.promfg.2018.03.137.
[48] P. Lai, "The literature review of technology adoption models and theories for the novelty technology," *J. Inf. Syst. Technol. Manage.*, vol. 14, no. 1, pp. 21–38, Apr. 2017, doi: 10.4301/S1807-17752017000100002.
[49] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quart.*, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.2307/249008.
[50] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, Feb. 2000, doi: 10.1287/mnsc.46.2.186.11926.
[51] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decis. Sci.*, vol. 39, no. 2, pp. 273–315, May 2008, doi: 10.1111/j.1540-5915.2008.00192.x.
[52] I. Ajzen, "The theory of planned behavior," *Org. Behav. Hum. Decis. Processes*, vol. 50, no. 2, pp. 179–211, 1991, doi: 10.1016/0749-5978(91)90020-t.
[53] E. M. Rogers, *Diffusion of Innovations*, 4th ed. New York, NY, USA: Simon and Schuster, 1995.
[54] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quart.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.
[55] D. L. Goodhue and R. L. Thompson, "Task-technology fit and individual performance," *MIS Quart.*, vol. 19, no. 2, pp. 213–236, 1995.
[56] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," *MIS Quart.*, vol. 36, no. 1, pp. 157–178, 2012, doi: 10.2307/41410412.
[57] R. L. Thompson, C. A. Higgins, and J. M. Howell, "Personal computing: Toward a conceptual model of utilization," *MIS Quart.*, vol. 15, no. 1, pp. 125–143, 1991, doi: 10.2307/249443.
[58] M. M. Alamri, M. A. Almaiah, and W. M. Al-Rahmi, "The role of compatibility and task-technology fit (TTF): On social networking applications (SNAs) usage as sustainability in higher education," *IEEE Access*, vol. 8, pp. 161668–161681, 2020.
[59] M. D. Williams, N. P. Rana, and Y. K. Dwivedi, "The unified theory of acceptance and use of technology (UTAUT): A literature review," *J. Enterprise Inf. Manage.*, vol. 28, no. 3, pp. 443–488, Apr. 2015, doi: 10.1108/jeim-09-2014-0088.
[60] J.-W. Lian, D. C. Yen, and Y.-T. Wang, "An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in taiwan hospital," *Int. J. Inf. Manage.*, vol. 34, no. 1, pp. 28–36, Feb. 2014, doi: 10.1016/j.ijinfomgt.2013.09.004.
[61] G. Chen, S. M. Gully, J.-A. Whiteman, and R. N. Kilcullen, "Examination of relationships among trait-like individual differences, state-like individual differences, and learning performance," *J. Appl. Psychol.*, vol. 85, no. 6, p. 835, 2000, doi: 10.1037/0021-9010.85.6.835.
[62] S. Kar, A. Kar, and M. P. Gupta, "Talent scarcity, skill distance and reskilling resistance in emerging digital technologies—Understanding employee behaviour," in *Proc. ICIS*, Dec. 2020, p. 11.
[63] W. M. Al-Rahmi, N. Yahaya, A. A. Aldraiweesh, M. M. Alamri, N. A. Aljarboa, U. Alturki, and A. A. Aljeraiwi, "Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use E-learning systems," *IEEE Access*, vol. 7, pp. 26797–26809, 2019, doi: 10.1109/ACCESS.2019.2899368.
[64] D. L. Coutu, "The anxiety of learning," *IEEE Eng. Manag. Rev.*, vol. 30, no. 4, p. 106, Mar. 2002, doi: 10.1109/emr.2002.1167289.
[65] J. Mokyr, C. Vickers, and N. L. Ziebarth, "The history of technological anxiety and the future of economic growth: Is this time different?" *J. Econ. Perspect.*, vol. 29, no. 3, pp. 31–50, Aug. 2015, doi: 10.1257/jep.29.3.31.
[66] C. Chifamba, "Career flexibility: A panacea to skills obsolescence," *Asian J. Educ. Social Stud.*, vol. 7, no. 4, pp. 12–16, May 2020, doi: 10.9734/ajess/2020/v7i430204.
[67] P. K. McClure, "'You're fired,' says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment," *Social Sci. Comput. Rev.*, vol. 36, no. 2, pp. 139–156, Apr. 2018, doi: 10.1177/0894439317698637.
[68] J. Lu, J. E. Yao, and C.-S. Yu, "Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology," *J. Strategic Inf. Syst.*, vol. 14, no. 3, pp. 245–268, Sep. 2005, doi: 10.1016/j.jsis.2005.07.003.
[69] F. D. Davis and V. Venkatesh, "A critical assessment of potential measurement biases in the technology acceptance model: Three experiments," *Int. J. Hum.-Comput. Stud.*, vol. 45, no. 1, pp. 19–45, Jul. 1996, doi: 10.1006/ijhc.1996.0040.
[70] M. E. Banks and R. J. Ackerman, "Ethnic and gender computer employment status," *Social Sci. Comput. Rev.*, vol. 8, no. 1, pp. 75–82, Apr. 1990, doi: 10.1177/089443939000800107.
[71] B. Ewenstein, B. Hancock, and A. Komm, "Ahead of the curve: The future of performance management," *McKinsey Quart.*, vol. 2, pp. 64–73, May 2016.
[72] T. R. Hinkin, J. B. Tracey, and C. A. Enz, "Scale construction: Developing reliable and valid measurement instruments," *J. Hospitality Tourism Res.*, vol. 21, no. 1, pp. 100–120, Feb. 1997, doi: 10.1177/109634809702100108.
[73] S. Stier, J. Breuer, P. Siegers, and K. Thorson, "Integrating survey data and digital trace data: Key issues in developing an emerging field," *Social Sci. Comput. Rev.*, vol. 38, no. 5, pp. 503–516, Oct. 2020, doi: 10.1177/0894439319843669.
[74] J. F. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, "An assessment of the use of partial least squares structural equation modeling in marketing research," *J. Acad. Marketing Sci.*, vol. 40, no. 3, pp. 414–433, May 2012, doi: 10.1007/s11747-011-0261-6.
[75] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, 4th ed. New York, NY, USA: Guilford Publications, 2015.
[76] B. M. Byrne, *Structural Equation Modeling With Mplus: Basic Concepts, Applications, and Programming*. Evanston, IL, USA: Routledge, 2013.
[77] S. Petter, D. Straub, and A. Rai, "Specifying formative constructs in information systems research," *MIS Quart.*, vol. 31, no. 4, pp. 623–656, 2007, doi: 10.2307/25148814.
[78] C. Fornell and D. F. Larcker, "Structural equation models with unobservable variables and measurement error: Algebra and statistics," *J. Marketing Res.*, vol. 18, no. 3, pp. 382–388, Aug. 1981, doi: 10.1177/002224378101800313.
[79] D. Gefen and D. Straub, "A practical guide to factorial validity using PLS-graph: Tutorial and annotated example," *Commun. Assoc. Inf. Syst.*, vol. 16, pp. 91–109, Jul. 2005, doi: 10.17705/1cais.01605.
[80] Y. K. Djamba and W. L. Neuman, "Social research methods: Qualitative and quantitative approaches," *Teaching Sociol.*, vol. 30, no. 3, p. 380, Jul. 2002, doi: 10.2307/3211488.
[81] C. Baker, J. Wuest, and P. N. Stern, "Method slurring: The grounded theory/phenomenology example," *J. Adv. Nursing*, vol. 17, no. 11, pp. 1355–1360, Nov. 1992.
[82] C. Goulding, "Grounded theory, ethnography and phenomenology," *Eur. J. Marketing*, vol. 39, nos. 3–4, pp. 294–308, Mar. 2005.
[83] B. E. Neubauer, C. T. Witkop, and L. Varpio, "How phenomenology can help us learn from the experiences of others," *Perspect. Med. Educ.*, vol. 8, no. 2, pp. 90–97, Apr. 2019.
[84] J. Kaivo-Oja, "Towards better participatory processes in technology foresight: How to link participatory foresight research to the methodological machinery of qualitative research and phenomenology?" *Futures*, vol. 86, pp. 94–106, Feb. 2017, doi: 10.1016/j.futures.2016.07.004.
[85] M. A. Almaiah and I. Y. Alyoussef, "Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of E-learning system," *IEEE Access*, vol. 7, pp. 171907–171922, 2019, doi: 10.1109/ACCESS.2019.2956349.
[86] M. Kuciapski, "How the type of job position influences technology acceptance: A study of employees' intention to use mobile technologies for knowledge transfer," *IEEE Access*, vol. 7, pp. 177397–177413, 2019, doi: 10.1109/ACCESS.2019.2957205.

[87] J. Herrero, A. Torres, P. Vivas, and A. Urueña, "Technological addiction in context: The influence of perceived neighborhood social disorder on the extensive use and addiction to the smartphone," *Social Sci. Comput. Rev.*, Dec. 2019, doi: 10.1177/0894439319896230.
[88] J. M. López-Bonilla and L. M. López-Bonilla, "Sensation-seeking profiles and personal innovativeness in information technology," *Social Sci. Comput. Rev.*, vol. 30, no. 4, pp. 434–447, Nov. 2012, doi: 10.1177/0894439311427246.
[89] H. E. Riquelme and R. E. Rios, "The moderating effect of gender in the adoption of mobile banking," *Int. J. Bank Marketing*, vol. 28, no. 5, pp. 328–341, Jul. 2010, doi: 10.1108/02652321011064872.
[90] P. K. H. Mo, V. W. Y. Chan, X. Wang, and J. T. F. Lau, "Gender difference in the association between Internet addiction, self-esteem and academic aspirations among adolescents: A structural equation modelling," *Comput. Educ.*, vol. 155, Oct. 2020, Art. no. 103921, doi: 10.1016/j.compedu.2020.103921.

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