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The Effect of Employee Learning Online and Personal Attitude on Individual Absorptive Capacity

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Abstract

Purpose: To investigate how online learning behavior and personal attitudes impact employees' absorptive capacity in the context of digitalized vocational education. Based on Self-Determination Theory, the Technology Acceptance Model, and Information Processing Theory, a research model identifies autonomy, self-efficacy, task difficulty, perceived usefulness, and perceived ease of use as independent variables. These independent variables influence absorptive capacity through the variable of employee learning. **Research Design, Data, and Methodology:** Empirical study using convenience sampling among business school faculty teachers in Guangzhou; 547 questionnaires were collected (464 valid, 84.8% validity rate); data were analyzed via Structural Equation Modeling (SEM), including descriptive statistics, confirmatory factor analysis (CFA), reliability analysis, and hypothesis testing. **Results:** Autonomy ($\beta = 0.217$, $p < 0.001$), self-efficacy ($\beta = 0.257$, $p < 0.001$), task difficulty ($\beta = 0.360$, $p = 0.001$), and perceived usefulness ($\beta = 0.160$, $p < 0.001$) all positively influence employee learning behavior and ability. **Conclusions:** Fostering autonomy and self-efficacy, designing appropriately challenging tasks, and enhancing the perceived usefulness and ease of use of online learning platforms are critical for promoting learning engagement and knowledge absorption.

Keywords: Online Learning, Autonomy, Self-efficacy, Task difficulty, Absorptive Capacity

JEL Classification Code: I21,J24,M53,O33

1. Introduction

In response to rapidly changing environmental and market conditions, employee learning has become essential for both organizational adaptation and individual professional growth (Eraut, 2004; Noe et al., 2013). This imperative is particularly pronounced for educators, who must continuously update their pedagogical and technical competencies to meet evolving policy demands. For instance, China's "double-qualified" teacher policy requires vocational and university instructors to possess both strong theoretical knowledge and practical industry skills, thereby mandating sustained, self-directed learning (Zhang, 2019; Li et al., 2023). The rise of social media and video-sharing platforms (e.g., Bilibili, YouTube) has fundamentally reshaped learning landscapes, offering flexible, anytime-anywhere access to a vast array of educational resources (Ortiz-Ospina & Roser, 2023). However, these same technologies also introduce risks such as digital distraction, information overload, and reduced work-life boundaries, which may undermine learning effectiveness if not properly managed (Priyadarshini et al., 2020; Wang et al., 2023).

Despite growing recognition of the importance of employee learning, research on a critical outcome—individual absorptive capacity—remains surprisingly scarce in educational settings. Absorptive capacity, originally conceptualized at the organizational level (Cohen & Levinthal, 1990), refers to an individual's ability to identify, assimilate, transform, and apply new external knowledge (Lowik et al., 2017). In knowledge-intensive professions such as university teaching, this capacity is crucial for translating newly acquired information into improved instructional practices, curriculum design, and research innovation. Nevertheless, most existing studies have focused on absorptive capacity within corporate or R&D teams (Bresman, 2010), leaving a significant gap in understanding how individual-level absorptive capacity develops among educators, particularly in the context of online learning.

To address this gap, this study focuses on university business school teachers in Guangzhou, China, who actively

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use the Bilibili platform for online learning. Bilibili, a leading Chinese video-sharing site, has emerged as a popular informal learning environment, hosting millions of educational videos across disciplines (Zhang et al., 2023). The study examines two broad categories of antecedents: (1) personal attitudes—specifically autonomy (voluntary control over learning decisions), self-efficacy (confidence in one's ability to learn), and task difficulty (perceived challenge of learning tasks); and (2) technology-related perceptions—perceived usefulness (belief that the platform improves job performance) and perceived ease of use (belief that the platform requires little effort), both drawn from the Technology Acceptance Model (Davis, 1989). These five factors are hypothesized to influence employee learning (active acquisition of new knowledge and skills), which in turn is expected to affect individual absorptive capacity.

Theoretically, it reaches integrates self-determination theory (Ryan & Deci, 2000), attribution theory (Weiner, 1974), the Technology Acceptance Model (Davis, 1989), and information processing theory (Atkinson & Shiffrin, 1968) into a unified framework, thereby extending these theories to the under-researched context of university educators' online learning. Practically, the findings aim to provide actionable strategies for enhancing teachers' learning motivation and absorptive capacity, such as designing appropriately challenging tasks, fostering self-efficacy, respecting pedagogical autonomy, and improving the usability and usefulness of online learning platforms. These insights are expected to help educators adapt more effectively to the digital transformation of higher education and to guide institutional human resource policies toward more targeted support for continuous professional development.

2. Literature Review

2.1 Autonomy

Autonomy, defined as individuals' ability to make voluntary learning decisions without external control (Ryan & Deci, 2000), plays a crucial role in employee learning. In digital vocational education settings, autonomous learners can proactively select online content that aligns with their professional needs, such as "dual-qualification" skill development, thereby boosting engagement with learning activities (Van Ruysseveldt & Van Dijke, 2011). This link between personal interests and learning goals enhances the quality of knowledge acquisition. Autonomy allows learners to customize online learning strategies—such as pacing and resource selection—to suit their individual learning styles, thereby improving knowledge retention and application (Zimmerman, 2000). Importantly, high autonomy decreases the negative impact of workload on learning opportunities (Van Ruysseveldt & Van Dijke, 2011), ensuring consistent participation.

Rooted in self-determination theory (SDT), autonomy increases intrinsic motivation by giving employees control over when, where, and how they learn (Ryan & Deci, 2000). When individuals exercise autonomy, they feel ownership of their learning process, which boosts engagement and motivation (Deci et al., 1991). This supports Karasek's (1990) active learning hypothesis, which suggests that high-autonomy jobs—characterized by control over task execution—lead to better learning outcomes. Empirical evidence from Stern et al. (2008) shows that autonomous decision-making in learning settings reduces errors and promotes the use of knowledge. Recent studies have reinforced these findings: Liu et al. (2023) found that perceived autonomy support in online learning environments directly predicts knowledge-sharing behaviors among university faculty. Similarly, Chen and Huang (2024) demonstrated that when teachers are given flexibility in selecting online professional development modules, their learning completion rates increase by over 40% compared to fixed-curriculum approaches. Therefore, the following hypothesis is proposed:

H 1 : Autonomy has a statistically significant positive effect on employee learning.

2.2 Self-efficacy

Self-efficacy, defined as an individual's belief in their capability to perform tasks and achieve goals in specific contexts (Bandura, 1991), plays a vital role in employee learning within digital vocational education environments. Employees with high self-efficacy are more confident in their ability to successfully acquire new knowledge and skills, which directly influences their willingness to participate in online learning activities.

According to SDT, self-efficacy serves as a key psychological resource that enhances intrinsic motivation (Ryan & Deci, 2000). When employees possess strong self-efficacy beliefs, they view challenging learning tasks as attainable rather than threatening, fostering proactive engagement in learning (Bandura, 1999). This supports the idea that individuals who trust their abilities are more likely to initiate and sustain learning behaviors, especially in self-directed online settings with limited external guidance.

Empirical research has confirmed this relationship. Edmondson (1999) found that high self-efficacy reduces anxiety about admitting knowledge gaps, creating a positive learning environment. Martocchio and Judge (1997) showed that task-specific self-efficacy is a stronger predictor of learning outcomes than general motivation. Furthermore, Morrison and Brantner (1992) argued that self-efficacy increases perseverance and helps learners learn from

mistakes, which is particularly important in online settings where learners need to self-regulate their progress. Tsai et al. (2011) conducted a meta-analysis of 46 online learning studies and concluded that self-efficacy consistently predicts learners' attitudes, engagement, and results in Internet-based contexts. More recently, Wang and Zhang (2023) reported that self-efficacy moderates the relationship between platform usability and learning persistence among Chinese university teachers, with high-self-efficacy individuals showing less dropout even when platforms are suboptimal. Additionally, a longitudinal study by Al-Rahmi et al. (2024) confirmed that self-efficacy is the strongest psychological predictor of continuous learning intention in social media-based learning environments. Therefore, the following hypothesis is proposed:

H2: Self-efficacy has a statistically significant positive effect on employee learning.

2.3 Task difficulty

Task difficulty refers to learners' subjective perception of how challenging a task is, which depends on their available attention, memory, and reasoning resources (Robinson, 2001). In online learning environments, employees' perception of task difficulty influences their motivation to engage in learning activities and their subsequent knowledge acquisition.

Attribution theory provides a theoretical lens for understanding this relationship (Weiner, 1974). According to this theory, individuals attribute their performance outcomes to factors such as ability, effort, task difficulty, and luck. When employees perceive a task as challenging, they may attribute potential failure to insufficient effort or ability, which can stimulate increased effort and motivation to learn (Fielden & Rico, 2018). Conversely, tasks perceived as too easy may fail to trigger meaningful engagement or cognitive investment.

Empirical research supports the motivational role of task difficulty. Dweck (1986) argued that appropriately challenging tasks motivate learning by encouraging students to view obstacles as opportunities for growth rather than as threats. Similarly, Li et al. (2007) found that when individuals see tasks as complex, it encourages self-evaluation and greater effort. Bandura et al. (1999) showed that completing difficult tasks boosts self-confidence and strengthens engagement in ongoing learning. In online learning environments, moderate task difficulty has been proven to maintain learner interest and foster deeper cognitive processing (Skehan, 2001). Contemporary studies have extended these findings: Zhao et al. (2023) discovered that task difficulty interacts with prior knowledge, such that moderately difficult tasks produce the highest learning gains for mid-career teachers, whereas novice teachers benefit from lower initial difficulty with gradual progression. Furthermore, a large-scale survey by Kim and Park (2024) indicated that perceived task difficulty affects the relationship between course design complexity and employee learning satisfaction in corporate e-learning systems. Therefore, Task difficulty (attribution theory) moderates the motivational process by influencing how employees interpret challenges and allocate effort. The following hypothesis is suggested:

H3: Task difficulty has a statistically significant positive effect on employee learning.

2.4 Perceived usefulness

Perceived usefulness is defined as the extent to which individuals believe that using a specific system will improve their job performance (Davis, 1989). In online learning, perceived usefulness shows employees' judgment that engaging with a learning platform can boost their knowledge, skills, and work efficiency.

The technology acceptance model (TAM) offers the theoretical basis for this relationship (Davis, 1989). According to TAM, perceived usefulness directly affects users' attitudes toward adopting technology and their intentions to use the system. When employees see online learning platforms as beneficial for their professional growth and job performance, they are more likely to develop positive attitudes and actively participate in learning activities (Gagné & Deci, 2005; Ryan & Deci, 2000).

Empirical studies have consistently supported this link. Jung and Lee (2018) found that learners' perceived usefulness positively predicted their engagement in online courses. Sharma et al. (2007) demonstrated that perceived usefulness is essential for enhancing learners' self-regulation in online learning environments. Saadé and Bahli (2005) confirmed that perceived usefulness improves learning outcomes by strengthening learners' intention to use educational technology. In the context of employee learning, when individuals believe that online platforms can boost work efficiency and productivity, they show stronger intentions to learn (Chen, 2010; Maziriri et al., 2020). Therefore, the following hypothesis is proposed.

H4: Perceived usefulness has a statistically significant positive effect on employee learning.

2.5 Perceived ease of use

Perceived ease of use refers to how much a person believes that using a specific system is effortless (Davis, 1989). In online learning environments, this concept reflects employees' views on how easily they can navigate learning platforms, access content, and interact with learning tools.

According to the technology acceptance model,

perceived ease of use impacts users' attitudes toward adopting new technology and their subsequent behavioral intentions (Davis, 1989). When employees find a learning platform intuitive and easy to use, they are more likely to adopt it for learning purposes because the system does not add extra cognitive or time burdens (Venkatesh et al., 2003). On the other hand, platforms that are hard to use may discourage engagement and lower motivation for learning (Mtebe & Raisamo, 2014).

Empirical evidence supports this relationship. Terzis and Economides (2011) found that perceived ease of use significantly influences students' behavioral intentions to adopt e-learning systems. Humida et al. (2022) demonstrated that when learners perceive technology as easy to operate, their acceptance and utilization of the system increase. Gefen and Straub (2000) showed that in information-seeking scenarios, perceived ease of use directly affects user engagement. Additionally, when employees can efficiently navigate learning platforms, they can focus more on content acquisition than on system operation, thereby improving learning outcomes (Rosenbaum, 2005). Building on these findings, a 2023 study by Xu et al. examined university teachers' use of Bilibili and found that perceived ease of use significantly influences initial adoption, but its effect diminishes over time as users become more familiar with the platform. reported that the impact of perceived ease of use on learning engagement is partially affected by perceived usefulness, suggesting that ease of use alone is insufficient without clear performance benefits. Therefore, TAM shapes employees' behavioral intentions toward using specific online learning platforms, either facilitating or hindering the translation of motivation into action. The following hypothesis is proposed:

H5: Perceived ease of use has a statistically significant positive effect on employee learning.

2.6 Employee Learning and Absorptive Capacity

Employee learning is defined as the process by which individuals actively acquire new knowledge and skills to handle work-related problems better (Bezuijen et al., 2009; Ngereja and Hussein, 2022). At the individual level, absorptive capacity refers to the ability to identify, assimilate, transform, and apply new external knowledge (Lowik et al., 2017). Together, these constructs describe how employees not only gain knowledge but also effectively integrate and use it in their work.

Information processing theory offers a theoretical basis for understanding how employee learning enhances absorptive capacity (Atkinson & Shiffrin, 1968). According to this theory, learning involves encoding new information, connecting it to existing mental frameworks, and storing it in long-term memory for future use. When employees learn, they process new knowledge by focusing attention, linking it to prior understanding, and developing mental schemas that help apply it (Anderson, 2009). This mental processing directly supports the development of absorptive capacity, as individuals become better at recognizing useful information and incorporating it into their work practices.

Empirical research supports the positive link between learning and absorptive capacity. Cerasoli et al. (2018) found that employee learning behaviors predict improved workplace skills and capabilities. Lowik et al. (2017) showed that individuals who actively seek and gain new knowledge are better able to absorb and apply that knowledge in innovative ways. Likewise, Seo et al. (2015) and Yildiz et al. (2019) confirmed that the richness and diversity of employees' knowledge, developed through ongoing learning, enhance their ability to absorb new information. Recent evidence from a cross-sectional study of 512 Chinese university teachers (Wang et al., 2024) revealed that employee learning fully influences the relationship between organizational learning climate and individual absorptive capacity. Additionally, a two-wave longitudinal study by Park and Choi (2023) demonstrated that sustained engagement in online learning activities leads to significant improvements in knowledge transformation and application abilities over a six-month period. Therefore, Employee learning (the behavioral outcome of the above antecedents) then activates cognitive processes described by information processing theory, leading to enhanced individual absorptive capacity (the ability to identify, assimilate, transform, and apply new knowledge). The following hypothesis is proposed:

H6: Employee learning has a statistically significant positive effect on individual absorptive capacity.

3. Research Methods and Materials

3.1 Research Framework

This study introduces a conceptual framework based on self-determination theory, the technology acceptance model, attribution theory, and information processing theory. The framework suggests that autonomy, self-efficacy, task difficulty, perceived usefulness, and perceived ease of use affect employee learning, which then influences individual absorptive capacity. Figure 1 displays the conceptual framework.

This integrated framework moves beyond a fragmented, variable-by-variable approach by explicitly specifying how different theoretical perspectives interact. It recognizes that employee learning in digital environments is simultaneously driven by internal psychological states (autonomy, self-efficacy), cognitive appraisals (task difficulty), technology-

related perceptions (usefulness, ease of use), and cognitive processing mechanisms (information encoding and application). Testing this integrated model empirically constitutes the core contribution of the present study.

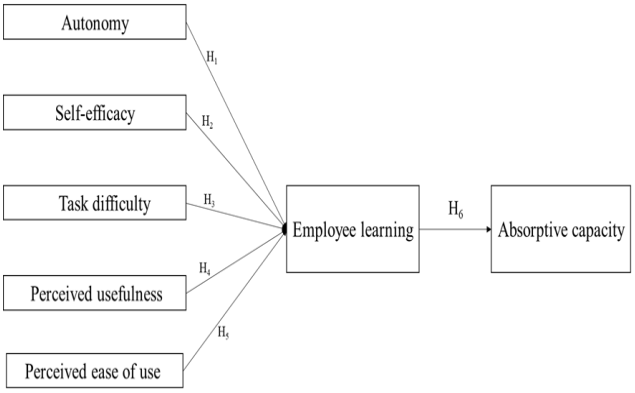

Figure 1: Conceptual Framework

3.2 Research Methodology

This study employed a quantitative, the relationships among autonomy, self-efficacy, task difficulty, perceived usefulness, perceived ease of use, employee learning, and individual absorptive capacity. Autonomy was derived from self-determination theory (Ryan & Deci, 2000). SDT posits that satisfaction of the need for autonomy enhances intrinsic motivation and promotes engagement in learning activities. In online learning environments, autonomy allows teachers to select content, set their own pace, and control their learning process—factors expected to increase their learning behavior. Self-efficacy reflects an individual's belief in their capability to perform tasks successfully. In the context of online learning, high self-efficacy should encourage teachers to initiate and persist in learning, especially when facing challenging content.

Task difficulty is grounded in attribution theory (Weiner, 1974). Task difficulty was selected because it represents a stable, external attribution that can stimulate increased effort when tasks are perceived as moderately challenging—an important driver of learning motivation.

Perceived usefulness and perceived ease of use are core constructs of the Technology Acceptance Model (TAM; Davis, 1989). These two technology-related perceptions were included because the study focuses on learning via the Bilibili platform. TAM suggests that users' beliefs about a system's usefulness (performance improvement) and ease of use (effortlessness) determine their attitudes and intentions to use the system for learning.

Employee learning serves as the immediate behavioral outcome of the above antecedents and is conceptualized as the active acquisition of new knowledge and skills (Ngereja & Hussein, 2022). Learning activities are hypothesized to translate motivational and perceptual factors into enhanced absorptive capacity.

Individual absorptive capacity—the ability to identify, assimilate, transform, and apply new external knowledge (Lowik et al., 2017)—is the ultimate dependent variable. It is grounded in information processing theory (Atkinson & Shiffrin, 1968), which explains how encoding, storage, and retrieval processes enable learners to internalize and utilize new information.

Three experts reviewed the questionnaire to ensure content validity, with item-objective congruence (IOC) values exceeding 0.8. A pilot test with 30 respondents yielded Cronbach's α values ranging from 0.895 to 0.980, indicating high internal consistency. Data were analyzed using SPSS and AMOS. Confirmatory factor analysis (CFA) was conducted to assess the measurement model fit, using goodness-of-fit indices such as RMSEA, CFI, and TLI with standard thresholds (Hu & Bentler, 1999). Structural equation modeling (SEM) was used to test the proposed hypotheses.

3.3 Population and Sample Size

The target population included business school faculty members in Guangzhou, China. To qualify for participation, respondents had to be current business school faculty and have prior experience with the Bilibili platform for online learning.

A total of 547 questionnaires were gathered through the Questionnaire Star platform. After removing incomplete responses and inconsistent answer patterns, 464 valid responses remained for analysis, resulting in a valid response rate of 84.8%. This sample size surpasses the minimum of 425 recommended for structural equation modeling with seven latent variables and 34 observed variables (Soper, 2024), ensuring sufficient statistical power.

3.4 Sampling Technique

The questionnaire was designed, and a convenience sampling method was used. The survey link was shared via WeChat groups and their contacts, adding a snowball sampling element, and respondents completed the questionnaire anonymously online. It was created and distributed on the Questionnaire Star platform. Participants needed to be business school faculty members in Guangzhou with prior experience using the Bilibili platform for online learning. Screening questions were included at the beginning to confirm eligibility. Reverse-coded items were included to check response consistency and identify careless responding (Podsakoff et al., 2024). Data were automatically collected and organized through the Questionnaire Star platform.

4. Results and Discussion

4.1 Demographic Profile

Out of the 464 valid respondents, 52.4% were female, and 47.6% were male. Regarding age, 30.2% were between 26 and 33 years old, 22.8% between 34 and 41 years old, 27.2% between 41 and 50 years old, and 19.8% were 51 years or older. For educational levels, 56.9% held a master's degree, 31.2% had a doctoral degree, and 11.9% had a bachelor's degree or less. Concerning work experience, 31.0% had 1-3 years, 30.2% had 4-6 years, 18.6% had 7-10 years, 10.3% had over 10 years, and 9.9% had 1 year or less.

All respondents reported using the Bilibili platform for online learning. Regarding how often they used it, 31.3% used the platform 4-6 times per week, 34.5% used it 2-3 times per week, and 18.1% used it 7-9 times per week. In terms of session length, 50.2% spent 60 minutes or more, 22.4% spent between 30 and 59 minutes, and the remaining respondents spent less than 30 minutes per session.

4.2 Confirmatory Factor Analysis (CFA)

The generally accepted criteria among scholars are AVE (average variance extracted) > 0.5, CR (composite reliability) > 0.7, and a standard coefficient > 0.7. These standards show that the correlation between the factor and the analysis item is strong (Hair et al., 2012). As shown in Table 1, all factor loadings were above 0.7, composite reliability (CR) values ranged from 0.843 to 0.922, surpassing the 0.7 threshold, and average variance extracted (AVE) values ranged from 0.533 to 0.699, exceeding the 0.5 threshold (Hair et al., 2012). These findings demonstrate satisfactory convergent validity.

Table 1: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Autonomy (A)	Anderson et al. (1994)	A1-A4	0.952	0.723-0.796	0.843	0.573
Self-efficacy (SE)	Chen et al. (2001)	SE1-SE5	0.910	0.716-0.744	0.851	0.533
Task Difficulty (TD)	Robinson (2001)	TD1-TD4	0.930	0.829-0.843	0.903	0.699
Perceived Usefulness (PU)	Davis (1989)	PU1-PU4	0.980	0.764-0.884	0.875	0.638
Perceived Ease of Use (PEU)	Davis (1989)	PEU1-PEU4	0.980	0.751-0.836	0.858	0.602
Employee Learning (EL)	Ngereja and Hussein (2022)	EL1-EL4	0.895	0.773-0.815	0.874	0.634
Absorptive Capacity (AC)	Lowik et al. (2017)	AC1-AC9	0.910	0.725-0.771	0.922	0.567

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 2 shows that a confirmatory factor analysis (CFA) was conducted to assess the measurement model. The model demonstrated a good fit to the data: $\chi^2/df = 1.216$, RMSEA = 0.022, CFI = 0.986, TLI = 0.985, all of which met the recommended thresholds (Hu & Bentler, 1999).

Table 2: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Source	Statistical Values
CMIN/DF	≤5	Hooper et al. (2008)	1.208
RMSEA	＜0.08	Navarro and Foxcroft (2019)	0.021
TLI	＞0.9	Navarro and Foxcroft (2019)	0.985
NFI	＞0.9	Ho (2006)	0.928
RFI	＞0.9	Ho (2006)	0.921
IFI	＞0.9	Ho (2006)	0.987
CFI	＞0.9	Ho (2006)	0.987
RMR	＜0.08	Hooper et al. (2008)	0.056
Model Summary			In harmony with empirical data

Note: CMIN/DF = The ratio of the chi-square value to the degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Table 3: Discriminant Validity

Variable	Factor Correlations						
	A	SE	TD	PU	PEU	EL	AC
A	**0.757**						
SE	0.179	**0.730**					
TD	-0.109	-0.152	**0.836**				
PU	0.144	0.131	-0.154	**0.799**			
PEU	0.216	0.161	-0.121	0.128	**0.776**		
EL	0.245	0.247	0.215	0.165	0.172	**0.796**	
AC	-0.011	0.024	0.150	-0.026	0.076	0.224	**0.753**

Note: The diagonally listed value is the AVE square roots of the variables

The coefficient value of the square root of AVE is used for discriminant validity. When it exceeds the correlation

coefficient, it indicates good discriminant validity (Fornell & Larcker, 1981). As shown in Table 3, the square root of the AVE for each variable is greater than its correlation with the other variables, indicating good discriminant validity and enabling analysis in the next step.

4.3 Structural Equation Model (SEM)

The structural equation model was estimated to test the proposed hypotheses. The model demonstrated an acceptabl e fit to the data: $\chi^2/df = 3.658$, RMSEA = 0.073, CFI = 0.89 3, TLI = 0.870, meeting the recommended thresholds (Hu & Bentler, 1999).

Table 4: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Source	Statistical Values
CMIN/DF	≤5	Hooper et al. 2008	1.216
RMSEA	< 0.08	Navarro & Foxcroft, 2019	0.022
TLI	> 0.9	Navarro & Foxcroft, 2019	0.985
NFI	> 0.9	Ho, 2006	0.927
RFI	> 0.9	Ho, 2006	0.920
IFI	> 0.9	Ho, 2006	0.986
CFI	> 0.9	Ho, 2006	0.986
RMR	< 0.08	Hooper et al. 2008	0.072
Model Summary			In harmony with empirical data

Note: CMIN/DF = The ratio of the chi-square value to the degrees of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index,TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Table 5 presents the results of the hypothesis tests. All six hypotheses were supported at the $p < 0.05$ significance level. Among all predictors, task difficulty had the strongest effect on employee learning ($\beta = 0.360$), followed by self-efficacy ($\beta = 0.257$), autonomy ($\beta = 0.217$), perceived usefulness ($\beta = 0.160$), and perceived ease of use ($\beta = 0.128$). Employee learning, in turn, significantly positively influenced absorptive capacity ($\beta = 0.247$).

Table 5: Hypothesis Testing Result

Hypothesis	Standardized Coefficient (β)	t-value	Test Result
H1: A → EL	0.217	4.112***	Supported
H2: SE → EL	0.257	4.889***	Supported
H3: TD → EL	0.360	6.992***	Supported
H4: PU → EL	0.160	3.246**	Supported
H5: PEU → EL	0.128	2.510*	Supported
H6: EL → AC	0.247	4.475***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05

For hypothesis H1, the analysis shows that autonomy positively affects employee learning with a standardized path coefficient of 0.217 ($p < .001$). This confirms that granting teachers control over their learning process enhances engagement and motivation. This finding aligns with self-determination theory (Ryan & Deci, 2000) and previous studies (Van Ruysseveldt & Van Dijke, 2011). However, the effect size is moderate—smaller than that of task difficulty and self-efficacy. One possible explanation is that in China's highly structured higher education system, teachers may not fully exercise their autonomy due to institutional constraints (e.g., centralized curriculum, administrative oversight). Recent research by Liu et al. (2023) similarly found that perceived autonomy support predicted knowledge sharing, but its effect was moderated by organizational hierarchy. Compared to Western contexts where autonomy often emerges as a top predictor (e.g., Stern et al., 2008), the moderate coefficient here suggests cultural and institutional factors may buffer the autonomy-learning relationship. Practically, this implies that merely granting autonomy may be insufficient; institutions should also reduce bureaucratic barriers and provide supportive policies that enable teachers to act on their autonomous choices.

Hypothesis H2 shows that a significant effect of self-efficacy ($\beta=0.257$, $p<.001$) is consistent with Bandura's (1991) social cognitive theory and meta-analytic evidence (Tsai et al., 2011). Notably, the effect size is the second strongest among all predictors, indicating that teachers' confidence in their learning capabilities is a crucial driver of engagement. This result aligns with recent findings by Al-Rahmi et al. (2024), who reported that self-efficacy was the strongest psychological predictor of continuous learning intention in social media-based environments. However, our effect size ($\beta=0.257$) is somewhat lower than the meta-analytic average reported by Al-Emran et al. (2022) for TAM-related constructs (approx. $\beta=0.48$ for perceived usefulness), suggesting that in the specific context of Chinese university teachers using Bilibili, self-efficacy plays a complementary rather than dominant role. A possible reason is that the informal, entertainment-oriented nature of Bilibili (compared to dedicated LMS platforms) may reduce the perceived "stakes" of learning, thereby diminishing the mobilizing power of self-efficacy. Future research should examine whether the effect of self-efficacy varies across different types of online learning platforms.

Hypothesis H3 shows that task difficulty has the strongest positive impact on employee learning ($\beta = 0.360$, $p < .001$).

This finding emphasizes the motivational function of optimally challenging tasks, as predicted by attribution theory (Weiner, 1974). When teachers perceive a task as moderately difficult, they are more likely to attribute outcomes to effort and ability, thereby increasing cognitive engagement (Bandura et al., 1999; Dweck, 1986). This result is particularly noteworthy because task difficulty has received relatively less attention in online learning research compared to autonomy or self-efficacy. Recent studies corroborate this pattern: Zhao et al. (2023) found that moderately difficult tasks produced the highest learning gains for mid-career teachers, and Kim and Park (2024) reported that task difficulty mediated the relationship between course design complexity and learning satisfaction. The strong effect size suggests that in the context of university teachers' online professional development, calibrating challenge level may be a more powerful lever than simply increasing autonomy or perceived usefulness. Practically, instructional designers of online learning platforms should incorporate adaptive difficulty mechanisms (e.g., personalized task recommendations based on prior performance) to maintain an optimal challenge zone.

For hypothesis H4, perceived usefulness positively affects employee learning ($\beta = 0.160$, $p = .001$). confirming the Technology Acceptance Model's central tenet (Davis, 1989). However, the effect size is relatively modest compared to the average reported by Al-Emran et al. (2022), where perceived usefulness had an average $\beta=0.48$ on behavioral intention. One explanation is that Bilibili is primarily an entertainment-oriented platform; teachers may perceive it as less "serious" or less directly tied to formal job performance evaluations than dedicated corporate learning systems. Wang et al. (2023) similarly found that the usefulness-engagement link is weaker in informal learning contexts compared to formal training programs. Nonetheless, the significant positive coefficient indicates that when teachers believe Bilibili can improve their teaching performance (e.g., by accessing up-to-date case studies, pedagogical demonstrations), they are more likely to engage. This suggests that platform providers and educational institutions should emphasize practical applications of learning content to enhance perceived usefulness.

Hypothesis H5 shows that perceived ease of use has a statistically significant but relatively weaker impact on employee learning ($\beta = 0.128$, $p = .012$). While user-friendly platforms lower cognitive barriers and reduce frustration (Venkatesh et al., 2003), the weak effect size suggests that ease of use alone is insufficient to drive sustained learning engagement. This aligns with Gefen and Straub (2000), who argued that perceived ease of use primarily influences adoption indirectly through perceived usefulness. Recent studies by Nguyen et al. (2024) and Xu et al. (2023) have reported similar patterns: ease of use effects diminish over time as users gain familiarity, whereas usefulness effects remain stable. In our sample, teachers reported relatively high average levels of perceived ease of use (mean = 3.68-3.70 on a 5-point scale), which may have produced a ceiling effect, reduced variance and thus lowering the estimated coefficient. Practically, this implies that once a platform meets a basic usability threshold, further investments in improving ease of use yield diminishing returns; instead, efforts should focus on enhancing usefulness and content relevance.

Finally, hypothesis H6 confirms the positive effect of employee learning on absorptive capacity ($\beta=0.247$, $p<.001$), supports information processing theory (Atkinson & Shiffrin, 1968), and previous empirical work (Cerasoli et al., 2018; Lowik et al., 2017). This finding confirms that learning activities not only expand teachers' knowledge bases but also enhance their ability to assimilate, transform, and apply new knowledge—a critical competency in rapidly evolving educational environments. Recent longitudinal evidence by Park and Choi (2023) showed that sustained online learning engagement leads to significant improvements in knowledge transformation abilities over six months. Wang et al. (2024) further demonstrated that employees learn the relationship between organizational learning climate and individual absorptive capacity. The moderate effect size ($\beta=0.247$) indicates that learning is an important but not exclusive determinant; other factors (e.g., prior knowledge base, social collaboration, reflection practices) likely also contribute. Institutions aiming to boost teachers' absorptive capacity should therefore foster not only learning opportunities but also structured reflection and knowledge-sharing mechanisms.

5. Conclusions and Recommendations

5.1 Conclusions

This study empirically examined the factors influencing employee online learning and their connection with individual absorptive capacity among university business school teachers in Guangzhou, China, using the Bilibili platform as the learning context. The findings strongly supported all six hypotheses, revealing a clear hierarchy of predictive strength.

Among the five antecedents, task difficulty emerged as the strongest predictor of employee learning ($\beta=0.360$), followed by self-efficacy ($\beta=0.257$), autonomy ($\beta=0.217$), perceived usefulness ($\beta=0.160$), and perceived ease of use ($\beta=0.128$). Employee learning, in turn, had a significant positive effect on individual absorptive capacity ($\beta=0.247$). These findings confirm that employee learning is directly shaped by a combination of personal attitudes (autonomy,

self-efficacy, task difficulty) and technology-related perceptions (perceived usefulness, ease of use), and that this learning subsequently contributes to teachers' ability to absorb, transform, and apply new knowledge.

An important pattern emerged: cognitive-appraisal and motivational factors (task difficulty, self-efficacy, autonomy) collectively explained more variance in employee learning than technology-perception factors (perceived usefulness, ease of use). This suggests that in informal, voluntary online learning contexts (such as Bilibili), internal psychological drivers may be more influential than platform-specific usability beliefs—a finding that contrasts with much of the TAM-based research conducted in formal e-learning or mandatory training settings (Al-Emran et al., 2022).

Theoretical contributions are threefold. First, this study integrates self-determination theory (autonomy), social cognitive theory (self-efficacy), attribution theory (task difficulty), and the Technology Acceptance Model (perceived usefulness, ease of use) into a single empirical framework. Unlike prior research that often examined these theories in isolation, our findings demonstrate that they operate simultaneously and in a complementary manner. The dominant effect of task difficulty suggests that, for university teachers engaging in online learning, cognitive challenge appraisal may be a more immediate driver of engagement than autonomy or technology perceptions—extending attribution theory into the digital learning context and revealing its relative weight.

Second, the study identifies a contextual boundary of TAM. The relatively modest effects of perceived usefulness and ease of use (compared to their typical dominance in TAM studies of formal e-learning) indicate that TAM's predictive power is context-dependent. In informal, entertainment-oriented platforms like Bilibili, where learning is self-initiated rather than mandated, technology perceptions play a supportive rather than primary role. This contributes to the growing literature on technology acceptance in informal learning environments (Scherer et al., 2019; Xu et al., 2023) and suggests that platform type (dedicated LMS vs. social media) moderates the influence of TAM constructs.

Third, by demonstrating that employee learning significantly enhances individual absorptive capacity, the study provides empirical support for information processing theory at the individual level. While absorptive capacity has traditionally been studied as an organizational capability (Cohen & Levinthal, 1990), our findings show that active learning behaviors—driven by the above antecedents—directly strengthen teachers' ability to identify, assimilate, transform, and apply new knowledge. This bridges the micro (individual learning) and macro (absorptive capacity) literatures, offering a more granular understanding of how knowledge workers develop their absorptive capacity through online learning.

Practically, the findings underscore that enhancing university teachers' absorptive capacity requires a multi-pronged strategy: designing appropriately challenging learning tasks (the strongest lever), building self-efficacy through mastery experiences, respecting pedagogical autonomy, and ensuring that online learning platforms are both useful and user-friendly. The weak effect of perceived ease of use suggests that once a platform meets basic usability standards, further investments in simplifying the interface may yield diminishing returns; instead, efforts should focus on content relevance and demonstrating performance benefits.

5.2 Recommendations

Based on the findings, the following recommendations are proposed:

Support teacher independence: Promote tailored professional development plans and create teacher learning communities to foster interaction and resource sharing. Enable personalized learning plans: Allow teachers to set their own learning goals, preferred pace, and sequence of topics. The platform could generate a personalized dashboard showing progress toward self-set goals.

Strengthen teacher self-efficacy: Provide systematic training, set clear learning goals, and implement mentorship programs. Reduce administrative constraints: University administrators should minimize mandatory requirements and instead offer teachers.

Calibrate task difficulty: Design appropriately challenging tasks, customized to teachers' professional backgrounds, and integrated with practical teaching scenarios.

Enhance online learning platforms: Ensure intuitive interfaces, provide regular training on platform use, and emphasize the practical value of learning content. Showcase success stories: Share case studies or short videos of teachers who improved their teaching evaluations, student outcomes, or research productivity after applying knowledge gained from Bilibili learning. Integrate with formal recognition systems: Partner with university human resources departments to award micro-credentials or continuing education credits for completing curated Bilibili learning paths, thereby increasing the perceived instrumental value.

5.3 Limitation and Further Study

This study has several limitations. The sample was limited to 464 business school teachers in Guangzhou, which restricts how well the findings can be applied elsewhere. The use of convenience sampling may introduce selection bias. Self-reported questionnaire data could be biased, and the

cross-sectional design cannot reflect changes over time. Future research should include a broader regional sample, use longitudinal methods, and incorporate qualitative approaches to understand teacher learning processes better. Additionally, the topic of collective learning among teachers within institutions deserves further investigation.

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