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Predicting Workforce Engagement towards Digital Transformation through a Multi-Analytical Approach

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Abstract: The shift towards sustainable and digital practices in organizations is transforming employees' mindsets and work performance. The digital transformation in academia is leading to meaningful changes in the behaviors and responsibilities of non-academic employees within organizations toward sustainable and responsible practices. By expounding insights into these views through social exchange theory (SET), this study aims to examine the key predictors of employee engagement (EE); namely, knowledge sharing (KS), employee mobility (EM), training and development (TD), and psychological empowerment (PE) in a digital workplace scenario. A quantitative survey based on convenience sampling was conducted to validate the research framework through partial least squares structural equation modelling (PLS-SEM). Accordingly, 205 responses were collected from the non-academic staff of universities in Klang Valley, Malaysia. Data analysis results showed that all hypotheses were significantly accepted. The impact of the model variables on employee engagement in digital transformation was found to be 75%, with employee mobility and knowledge sharing being the most prominent factors. Multigroup analysis (MGA) and importance-performance map analysis (IPMA) were additional analytical tools applied to reinforce the survey findings further and provide more comprehensive insights into employee engagement across different departments within the organization. The findings also showed the robustness of social exchange theory in digital business practices. This research offers novel and innovative perspectives on the impact of various factors (KS, EM, TD, PE) on employee engagement during digital transformation and how they mold employee behavior toward driving productive and responsible outcomes.

Keywords: employee engagement; digital transformation; non-academic staff; employee mobility; knowledge sharing; PLS-SEM; MGA; IPMA

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1. Introduction

The subtle nature of humans has maintained a resistive approach toward change since the beginning of early civilizations. The concept of work was centered around activities such as farming, construction, and resource mobilization, which provided compensation for necessities such as food, shelter, clothing, and more. Kings, lords, and authorities of old often compelled their subjects to perform these necessary tasks through force. This was also evident in the construction of the Pyramids of Giza in Egypt, one of the ancient world's most magnificent structures, built at the cost of countless lives lost to grueling labor conditions. As humanity progressed with advancements in education, infrastructure, lifestyle, social systems, and governance, the values associated with work were also shaped more decently and healthily. The abolition of slavery, the introduction of labor laws, and the United Nations' Sustainable Development Goals (SDGs) are the most significant contributions to ensuring the safe and sustainable management of the human workforce. Similarly, technological advancements have driven traditional workplace scenarios towards digital, virtual, and collaborative modes. To drive productive outcomes and stay competitive with industry players, organizations invest significant resources in innovation management, process improvement, and employee training and development to facilitate digital transformation [1].

Technological transformation is captivating organizational operations, causing them to transition from the conventional way of doing business to a digital and sustainable one. Such transmuting of the business operations to digital modes manifests in computerized machinery for the employees' activities and customers' services. However, to reap the benefits of digital transformation on a long-term basis through engaging human capital is quite different from installing the digital system and tangible resources [2]. In the traditional business model, workforce engagement at conventional workplaces was influenced by factors such as job satisfaction, rewards and recognition, bonuses, promotions, supervisor support, training and development, and more. However, the impacts of volatile scenarios of rapid technological integration on the nature of skill management and the workplace have indicated the need for contemplating and grasping the factors involving technology management for engaging the workforce. With the increasing role of information technology in organizations, the traditional factors of workforce engagement may not be as effective, given the changing nature of the workplace, type of organizational activities, interaction among business units, organizational culture, and connectedness [3]. The approach to human labor has undergone a profound transformation, evolving from coercion to voluntary involvement. The modern workplace recognizes and considers employees' cognitive and situational factors, departing from the harsh realities of the past and embracing a more compassionate and innovative approach. By pondering such an analogy, implementing digital systems for work has less to do with the type of installed machinery and more to do with employees' level of productivity and engagement through a collaborative work approach [2].

In this scenario, an organization's human capital is crucial, as a report by Gartner [4] indicated that 83% of organizations failed to achieve their goals regarding digital transformation due to a lack of employee involvement in technology-driven business processes. A Microsoft study uncovered a prevalent sentiment among employees, with 61% confessing that implementing technology at their organization stirs up anxiety. Additionally, nearly half of all staff members, 49%, expressed fear regarding the ramifications of digital transformation in the workplace. Consequently, their motivation levels during work tasks decreased, leading to lower productivity and decreased commitment from employees in the organization [5]. Therefore, the challenge of engaging employees in a digitally-enabled workspace needs to be investigated by elucidating the cognitive and circumstantial determinants of the workforce [2].

The integration of Industry 4.0 (IR4.0) and the impact of the COVID-19 pandemic have compelled a move towards a more digital and virtual environment across various spheres of life, including business, governance, and education [1,6–9]. Within education, remote learning via online classes and virtual sessions is becoming increasingly popular, yet the critical role played by non-academic staff in maintaining the longevity of organizations cannot be overstated [10]. Their responsibilities in managing and facilitating behind-the-scenes organizational tasks contribute significantly to the change in management process and organizational growth. To enhance an organization's efficiency, it is crucial to consider the non-academic staff's perception of their work environment, motivation, benefits, and ways to foster their engagement in the workplace [11]. By considering the part employees play in digital transformation, the involvement of non-academic staff in the education sector also plays a crucial role in successfully integrating digital technologies in the workplace. The contribution of non-academic staff to academic ranking and institutional reputation may be limited [12]. However, the involvement of a motivated workforce is a strong indicator of organizational growth and development, and the implication of an engaged workforce strongly confers the signals of organizational development. The engagement of non-academic staff is assessed through evaluations of motivation, working conditions, benefits, career development and growth opportunities [13], knowledge management, training, and leadership roles [14]. The validation of social exchange theory (SET) for understanding the engagement factors of non-academic staff has also manifested in organizational development [15].

Within the context of a sustainable organization, numerous factors impact employee engagement. For example, work with supporting knowledge sharing is always beneficial for the organization, leading to engagement and a surge in employee motivation [16]. The Deloitte 2016 Millennial survey reported that 75% of millennials discoursed that they would prefer to do office tasks frequently from home or other places where they feel more creative and innovative [17], which portrays the significance impact of employee mobility on employee engagement. As digital transfusion in businesses requires up-to-date skills and business processes for the workforce, there is high demand for essential training and development programs [18]. These manage the employees during organizational changes and ensures their keen interest in being skilled in keeping stride with modern workplace requirements [19]. At the same pace as engaging workforces in digitally enabled workplace settings, psychological empowerment enables the workforce to perform their work more productively and innovatively. As Aldabbas et al. [20] explored, the individual's job roles and their internal motivation, coupled with a sense of control in performing organizational tasks through constructive involvement, tend to orchestrate positive relations with engagement at the workplace. Correspondingly, using SET in examining different factors for employee engagement, previous studies pinpointed how such factors predict employee attitude and intention towards digitally enabled organizations [21]. For instance, SET argues that dealing with psychological work associations is parallel to interpersonal relations, which mainly incorporate the individual- and organizational-level interactions of employees in the modern workplace [21]. Knowledge sharing is also prefaced on SET to explain individual behavior [22]. SET also provides a deeper insight into training and development, with employee mobility used to elucidate employee behavior at the workplace [23].

Since digital transformation is rapidly reshaping the majority of sectors [24], a sense of urgency regarding employee connectedness has become crucial for the current organizational change [25]. However, there are certain aspects that previous studies could not address, such as the collective contemplation of flexible working conditions, disseminating skillful information among peers, empowering the employees with a sense of control in digitally enabled business activities, and managing the talent through new skills, learning, and development. Previous research on non-academic staff has been lacking in its examination of the factors affecting employee engagement in digital transformation [12,14,15,26]. This is a pressing issue, as important questions remain unanswered: what are the key drivers of employee engagement that support digital transformation for non-academic staff, and how does their perception of their job role and work environment impact their engagement in this process? By considering these elements and aspects of employee behavior, the authors believe that valuable insights can be gained to help stakeholders develop strategies for engagement and retention in digital transformation. Moreover, assessing employee engagement (EE) in the digital transformation era on a departmental basis is important in ensuring the success of these initiatives. Previous studies have also neglected to examine the impact of digital transformation on different departments within an organization [10–15,26]. By gaining a deeper understanding of these effects, decision makers can adopt a targeted approach to overcoming the challenges they encounter. Initially, this will allow for a better understanding of departmental differences, including their unique cultures, work processes, and resources, which can impact their ability to adopt and implement digital transformation initiatives. By evaluating EE on a departmental level, universities can identify which departments are leading the way and which may need additional support. Furthermore, having these data also enables the more effective allocation of resources. If a department is struggling with low EE levels in the face of digital transformation, additional resources can be directed towards overcoming obstacles and ensuring success. Finally, evidence-based decision making is key in navigating the complex challenges of the digital era. By studying the impact of digital transformation on a departmental basis and gathering data and insights on EE levels, universities can make informed decisions that support their employees and drive positive outcomes. For such purpose, multigroup analysis (MGA) [27] and importance-performance map analysis (IPMA) [28] would yield resourceful inferences that have yet to be explored.

By accumulating the topical engagement factors under the same umbrella, this study proposed the conceptual framework of employee engagement on digitally enabled educational institutional platforms through knowledge sharing, psychological empowerment, employee mobility, and training and development towards the prediction of non-academic employees' engagement. With a fresh perspective, this study sheds light on the often neglected aspect of employee engagement that could help to understand the workforce perspective in digital transformation. The significance of this hypothesized model inclined towards a better understanding of the modern and sustainable way of work and labor connection. The study will present the backgrounds of engagement at the workplace as an innovative contribution, and this novel addition to the sustainable perspective of employee engagement will manifest in pathways for organizational decision makers. The research contemplated the empirical survey to grasp the inferences of the proposed relationships between variables. The PLS-SEM, MGA, and IPMA were implied to exhibit the results of quantitative analysis from surveyed data.

2. Literature Review

2.1. Social Exchange Theory (SET)

SET is one of the most prominent paradigms for understanding employee behavior. It suggests that social behavior is the outcome of an exchange procedure. According to Saks [29], SET proposes a theoretical foundation for explaining why staff are more or less involved in the workplace. The author opined that a theory of employee engagement (EE) with a more robust theoretical rationale had been found within SET. Aldabbas et al. [20] argued that the cost–benefit relationship promotes directing a set of exchange approaches, and SET likewise fosters employees' expectations, leading to their desired actions and behavioral outcomes such as knowledge sharing (KS) and innovativeness. Based on this statement, workforces attach themselves to the organization with precise knowledge, wishes, and missions; they want an office environment to properly use their knowledge, content their needs, and fulfill their missions. In addition, employee mobility (EM) can be clarified within SET. For example, Koon and Chong [30] posited that staff who prefer a flexible workplace where they can work from anywhere like to be highly involved in their organizations. On the other hand, Lai et al. [31] noted that organizational members who want to improve their skills via training and development (TD) programs are likely to be highly engaged in their organization. A study by Chernyak-Hai and Rabenu [21] revealed that as organizational relationships are still based on cost–benefit interaction, SET may provide enough insight into the exchange relationship within digital workplace mechanisms. As has been discussed by Maan et al. [32], when a workforce is more psychologically empowered, he/she will be more satisfied with job duties, thus establishing social exchange relations. Therefore, as SET provides the theoretical foundation for explaining the variability of staff engagement, this study develops the research framework to determine four factors (i.e., KS, EM, TD, PE) affecting EE in the digital workplace under the norms of SET.

This study is conclusively grounded in the social exchange theory (SET), a broad and substantial theory that has proved its ability to account for diverse behavioral response patterns. According to SET, when organizations treat their employees well, the likelihood of receiving positive responses increases; this is known as reciprocating behaviour [33]. SET also clarifies that organizations can benefit significantly when employees operate in a work culture that encourages open knowledge sharing [34]. Moreover, a recent study evinced that providing employees with training and development opportunities helps them acquire new knowledge and skills and increases their dedication and commitment to their work [35]. Additionally, when employees receive support from their organization and feel a sense of belief in and control over their work, they are more likely to exhibit positive responses while completing their work [20,32]. Furthermore, providing employees with the flexibility to work from anywhere using technology leads to a greater sense of devotion towards their job roles [36]. All of the above communal responses are deeply rooted in the concepts of SET, which serves as a sturdy theoretical foundation for this research. While other studies have investigated several factors such as training and development [35], knowledge sharing [20], and psychological empowerment [32,37,38] to elucidate employees' reciprocating behavioral outcomes (i.e., organizational commitment, innovative work behaviour, job satisfaction, and work engagement), such studies entirely rely on the powerful concept of SET to illuminate these good patterns of employee behaviors.

2.2. Knowledge Sharing

In our knowledge-based economy, knowledge sharing (KS) has become more and more important to digital workplaces. KS is a social procedure where individuals desire to share their knowledge and skills with others. According to Ahmad [39], KS is the exchange of work-related skills, instruction, and the ability to guide and work together to carry out job duties, solve problems, and develop innovative thoughts. Technological transformation in an organization is an all-inclusive activity consisting of systems, devices, techniques, and knowledge that support conveying data and providing information [40]. Deloitte's survey exposed that when knowledgeable employees have access to a digital workplace, they are up to 17% more pleased with the workplace [17]. By collecting 250 raw responses from non-academic staff employed at different Malaysian universities, a recent study showed that employees' knowledge-sharing intention is positively linked to employees' positive behavioral outcomes. The study further confirmed that most of the non-academic staff of Malaysian universities were eager to share their knowledge to gain organizational attainments [26]. According to Juan et al. [41], the KS approach helps an organization to engage its potential staff in job duties, which supports the organization in attaining and sustaining competitive advantages. The authors provided evidence that KS has a significant and positive effect on EE. Moreover, quantitative research conducted on 191 employees in Saudi Arabia revealed that KS is positively and significantly associated with EE [42]. According to the preceding explanation, this study develops the hypothesis as follows:

Hypothesis 1 (H1). *Knowledge sharing (KS) has a positive effect on employee engagement (EE).*

2.3. Employee Mobility

Employee mobility (EM) previously referred to the movement of employees to other locations to perform work assignments for a specific period. However, its definition has expanded to include both the physical and virtual mobility of staff [43]. The author further explained that EM is the unique trend of a digital workplace, known as "bring your own device (BYOD)" or work from anywhere, i.e., at home or in other locations. Therefore EM or staff relocation is defined as the process of transferring skilled workforces from one place to another. EM overlays the process of digitization, which supports an organization in continuing its business procedures and leads to a boost in EE [43]. In a strategic analysis, Rajagopal [44] emphasized that to enhance employee attachment, employers can improve staff-oriented HR strategies by mobility in the organizational or industrial system. The study surveying 126 working staff in four multinational companies found that around 52% of respondents believe they would be highly productive if permitted to work with their own devices from any place [45]. Edwards [46] highlighted that EM would increasingly act as a cognitive process, empowering workforces to gain innovativeness quickly, which in turn brings better productivity at both individual and organizational levels. Based on 394 survey responses and 25 interviewers, Göçer et al. [36] found that over 50% of respondents regularly work at a fixed desk. However, the authors further confirmed that flexible and mobile workers are more satisfied than those at fixed desks. These mobile workers lead to a more congenial work environment and increase their productivity. Based on these discussions, we hypothesize the subsequent relationships in the non-academic staffs' engagement context:

Hypothesis 2 (H2). *Employee mobility (EM) has a positive effect on employee engagement (EE).*

2.4. Training and Development

Training refers to the process of employees learning methods provided by employers to permanently enhance their job-related skills and knowledge [47]. Meanwhile, DeCenzo [48] defined development as employees gaining knowledge and skills, which increases their capacity to meet the variations of job demands. Since technology is considered part and parcel of organizational development [49], training and expert workers are required to support technology-oriented workplaces in the twenty-first century. For instance, an integrated curriculum, namely "the Digital Schoolhouse London Programme", was launched in the UK to help teachers at primary and secondary levels by providing an innovative computing course. This course was very effective, with over 600 teachers actively partaking in London zones [49]. Hence, organizations need better training and development (TD) opportunities to adapt to technology transmission. Implementing proper training and development (TD) programs for digital skills not only enhances and updates employees' knowledge and skills but also facilitates employee engagement (EE) [50]. Using SET as their theoretical framework, Khan and Iqbal's [51] empirical research on 313 Pakistani employees found that high levels of employee commitment to the organization have been attained because of successful TD programs. Another piece of research evidence suggests that TD positively affects employees' capacity to perform well, thus enhancing their engagement level in the workplace [37]. Therefore, the following hypothesis of this study was formulated regarding non-academic staffs' engagement context:

Hypothesis 3 (H3). *Training and development (TD) has a positive effect on employee engagement (EE).*

2.5. Psychological Empowerment

Psychological empowerment (PE) has been recognized by practitioners as a vital factor in EE. It plays a significant role in nourishing employee behavior. According to Spreitzer [52], PE refers to a person's emotional state, categorized as a feeling of authority with high inspiration and high capability for fulfilling expectations regarding the organization. Workers with feelings of autonomy, competency, and connection towards job duties are essential for future workplaces and greater employee wellbeing at work [1]. A study conducted by Meng and Sun [53] confirmed that PE is positively linked with EE in the workplace. Drawing on SET, Rehman et al. [23] found that PE strongly correlates with employees' outcomes. Similarly, based on SET, a cross-sectional study conducted by Arefin et al. [37] surveying 287 employees confirmed a positive correlation between PE and EE. Owan et al. [54] showed that PE is the sturdiest forecaster of academic staff commitment. Furthermore, as the intersection of the material worlds has existed in today's organizations, employees' psychological attachment in the modern workplace may result in a positive effect on employee outcomes [17,20,55]. Based on the existing research, we state the following hypothesis regarding non-academic staff's engagement context:

Hypothesis 4 (H4). *Psychological empowerment (PE) has a positive effect on employee engagement (EE).*

2.6. Research Framework

Based on the above deliberations, we have depicted the following research framework (Figure 1), which integrates four factors—namely, knowledge sharing (KS), employee mobility (EM), training and development (TD), and psychological empowerment (PE)—that influence the EE of non-academic staff in the digital workplace.

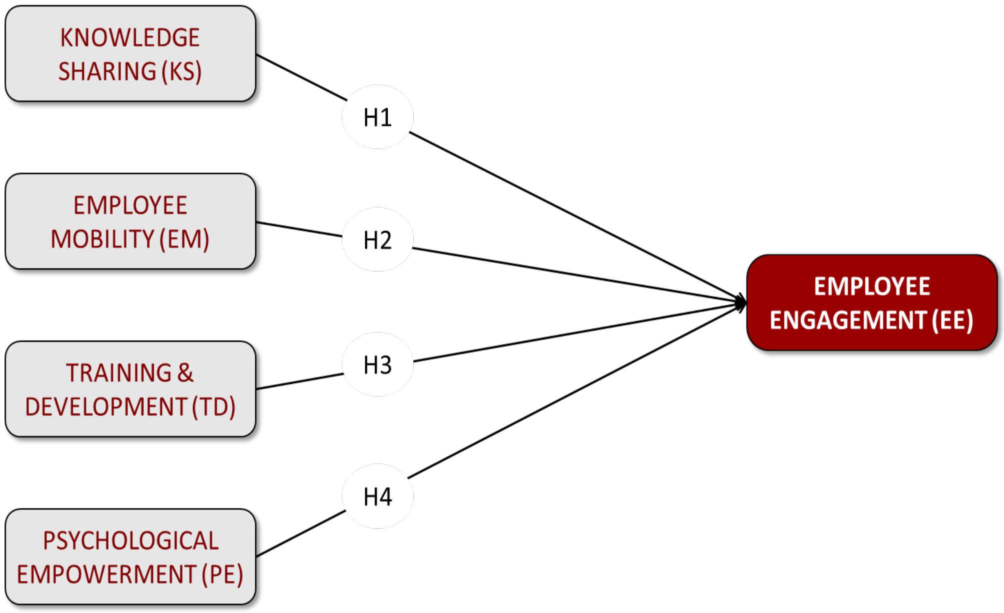

Figure 1. Research framework.

3. Methodology

This study employed a quantitative research design, adopting a positivist paradigm and a deductive approach. The research strategy involved conducting a survey with a cross-sectional approach [56]. The positivist paradigm seeks to establish causality between variables. The hypotheses were developed using the social exchange theory (SET), which was approached through the deductive method. A survey-based, cross-sectional research design was utilized to gather data. The study data were collected from the non-academic employees of the different educational institutes in Klang Valley using online survey forms. During uncertain times, such as the ongoing pandemic of COVID-19, reaching the targeted participants from the wider population can become challenging. In such scenarios, non-probability sampling methods such as convenience sampling can be ideal [57]. To ensure safety and accessibility, convenience sampling was utilized, which is a cost-efficient, uncomplicated, and swift way to gather information [58]. Due to the pandemic restrictions, in-person data collection was impossible, so an online survey was used instead. The survey was sent to working non-academic staff members from various departments at higher education institutes through various contacts. The data gathering took place from January to September 2021. As per the guideline of Kline [59], the goal was to collect at least 200 responses to ensure that the sample size was large enough to draw meaningful conclusions from the collected data. The survey ensured the anonymity and confidentiality of all participants. In the end, 205 responses were received.

The questionnaire consisted of two sections. The first section focused on each respondent's personal information, including demographic information such as gender, age, race, educational background, length of service, job level, and department. The second section consisted of 39 statements on a five-point Likert scale (i.e., strongly disagree = 1, strongly agree = 5). Seven items for KS and six for EM were adapted from Juan et al. [41] and i4cp [60], respectively. For measuring TD, one item, including skill enhancement, was adopted from Edgar and Geare [61], while four items were related to professional growth and personal growth, adopted from Siddiqui and Noor-us-Sahar's [62] research. PE was measured using Spreitzer's [52] scale, including 12 items. Finally, EE was determined by adopting nine items from Utrecht Work Engagement Scale [63]. All items are listed in Appendix A.

For the data analysis, multiple techniques were utilized through SmartPLS v3, including partial least squares structural equation modeling (PLS-SEM), multigroup analysis (MGA), and importance-performance analysis (IPMA). PLS-SEM is a statistical approach to modelling complex relationships between latent variables and their indicators. It is beneficial for use in research in fields with small sample sizes and when the relationships between variables are not well understood. This study used PLS-SEM to examine the relationships between the model variables based on 39 statements on the Likert scale [64]. MGA was performed to compare the results of multiple groups, such as different department subgroups. This technique allows for the examination of group-specific relationships and differences in the results between groups. MGA was justified in this study to provide a more nuanced understanding of the results and to determine if there were any significant differences between subgroups [27]. IPMA is a tool used to evaluate various factors or variables' relative importance and performance. In this study, IPMA was used to identify the most important factors that contributed to the survey results and to assess the relative performance of these factors in different groups. This analysis provided insights into the results' key drivers and helped prioritize areas for improvement [65,66]. The study also employed the common method bias (CMB) correction to ensure that the results were not influenced by the data collection method and that the findings were made more robust [28]. Moreover, the PLS-Predict technique was also implied to make predictions about the results based on the findings of the PLS-SEM analysis [67].

4. Results

4.1. Demographic Results

The demographic results (Table 1) revealed that a total of 118 male and 87 female respondents were surveyed; most of them belonged to the age group of 31–35 years. With respect to their race, most of the participants were Malay (52%). Most of them held an academic degree in higher education—77% had a bachelor's degree, while 17% had a master's degree. The majority of them had 6–10 years of job experience (54%), followed by less than one year (3%), 1–5 years (33%), and above ten years (10%). Regarding job level, 35% of participants were senior-level officers, while the remaining 65% held either executive or managerial roles.

Table 1. Demographic results.

Respondents' Profile	N	%	Respondents' Profile	N	%
Gender:			Tenure:		
Male	118	58	<1 year	7	3
Female	87	42	1–5 years	67	33
Age:			6–10 years	110	54
20–25	12	6	>10 years	21	10
26–30	27	13	Job level:		
31–35	96	47		49	24
36–40	65	32	Senior Officer	71	35
>40	5	2	Middle Manager	52	25
Race:			Manager	33	16
Malay	107	52	Department		
Chinese	57	28	Admission	52	25
India	26	13	IT	79	39
Others	15	7	Finance	34	17
Education:			HR	21	10
Diploma	13	6	Marketing	19	9
Bachelor	157	77			
Master's/Others	35	17			

4.2. Common Method Bias (CMB)

Common method bias (CMB) refers to the potential for systematic errors in data collected through a single method, such as self-report surveys, leading to an overestimation of the relationship between variables. This can occur due to factors such as participants responding in a socially desirable manner or their responses being influenced by their current mood [68]. To address this issue, researchers have employed Harman's single factor test to identify whether a single common factor is responsible for the correlation between variables. The test was implemented utilizing five model factors; namely, knowledge sharing, employee mobility, psychological empowerment, training and development, and employee engagement, referring to a study by [69]. The factors were loaded into a single factor and the resulting assessment revealed that the highest variance explained by the newly generated factor was 40.465%, which is below the threshold value of 50% [70]. This indicates that there were no issues of CMB present in the collected data.

4.3. PLS-SEM

Employing the SmartPLS software Version 3.3, the partial least squares structural equation modelling (PLS-SEM) approach was used to estimate the path model in exploring the inter-relationships of the latent variables [64]. Reliability, validity, and outer loading tests were conducted to estimate the measurement model. Additionally, the structural model was assessed to test the proposed hypotheses. The PLS-SEM method was applied because it deals with less imposed constraints on the distribution of the population and the sampling procedure. It is an effective approach for resolving multicollinearity issues [67].

The internal consistency of every construct was measured using Cronbach's alpha (α) and composite reliability (CR). The values of Cronbach's alpha and CR for each variable greater than 0.80, as presented in Table 2, showed a highly acceptable range of internal consistency [64]. The average variance extracted (AVE) was measured to assess convergent validity. The AVE value should be a minimum of 0.5 or higher to establish convergent validity [64]. Table 2 illustrates that the AVE values of all constructs meet this minimum requirement. Further, the relevant assessment criteria for outer loadings, indicating a sufficient level of reliability, should be 0.70 or above [64]. Table 2 represents that all of the outcomes of assessment criteria for outer loadings met the 0.70 thresholds, except for three items, i.e., KS7, PE5, and PE10. According to Soelton et al. [71], outer loading thresholds of 0.50 to 0.60 are still acceptable. Therefore, these three items are considered valid. Moreover, variance inflation factor (VIF), a measure of the amount of multicollinearity, of each item was determined in the measurement model. A threshold of VIF < 5, as shown in Table 2, indicates an acceptable level of multicollinearity [64]. Lastly, we analyzed the Heterotrait-Monotrait (HTMT) ratio to measure the discriminant validity. Our findings (Table 2) indicated that all HTMT values were $\leq$0.85, providing support for measuring discriminant validity [72].

Path analysis was assessed using the PLS-SEM technique to test each hypothesis (Figure 2). Table 3 displays the results of path analysis. Each hypothesis is shown in the number of steps. In the PLS-SEM for path analyses, statistically significant (p-value < 0.05 and t-value > 1.96) effects of KS, EM, TD, and PE on EE were orchestrated by confirming the proposed model hypotheses H1, H2, H3, and H4. Additionally, Table 3 demonstrates that KS, EM, TD, and PE together account for approximately 76% of the variance in the endogenous variable (EE), suggesting that these four factors are critically relevant predictors in positively changing EE. Moreover, Table 3 displays the f^2 effect size. A high f^2 effect size was found for the path EM $\rightarrow$ EE (0.424). A low f^2 effect size was found for the relationship KS $\rightarrow$ EE (0.118). The f^2 effect sizes for TD $\rightarrow$ EE (0.047) and PE $\rightarrow$ EE (0.070) in the structural model were found to be relatively weak but acceptable because the value of effect size was greater than 0.02 [64]. Regarding model fit in PLS-SEM, the SRMR (standardized root mean square residual) and NFI (normed fit index) values were considered to overcome the model misspecification [73]. In this research, a SRMR value of 0.059 indicates a good fit since it is below the threshold value of 0.08. Moreover, a NFI value of 0.766 indicates a relatively poor fit, as its value should be between 0 to 1 and is better when nearer to 1 [74].

Table 2. Reliability, validity, HTMT ratio, outer loading, and VIF results.

Construct	Items	α	CR	AVE	Outer Loadings	VIF	HTMT Ratio				
							EE	EM	KS	PE	TD
Employee Engagement (EE)	EE1 EE2 EE3 EE4 EE5 EE6 EE7 EE8 EE9	0.908	0.925	0.579	0.761 0.730 0.781 0.790 0.811 0.831 0.701 0.707 0.723	2.031 1.934 2.356 2.308 2.409 2.855 1.715 2.089 1.945					
Employee Mobility (EM)	EM1 EM2 EM3 EM4 EM5 EM6	0.895	0.920	0.656	0.837 0.827 0.782 0.803 0.822 0.787	2.553 2.364 1.957 2.079 2.363 1.953	0.843				
Knowledge Sharing (KS)	KS1 KS2 KS3 KS4 KS5 KS6 KS7	0.864	0.896	0.554	0.703 0.787 0.805 0.730 0.785 0.752 0.633	1.801 2.026 2.253 1.706 1.998 1.781 1.375	0.853	0.804			
Psychological Empowerment (PE)	PE1 PE2 PE3 PE4 PE5 PE6 PE7 PE8 PE9 PE10 PE11 PE12	0.922	0.933	0.540	0.770 0.734 0.766 0.760 0.686 0.709 0.762 0.721 0.747 0.625 0.750 0.772	2.504 2.349 2.340 2.816 2.007 2.154 2.446 2.219 2.294 1.644 2.354 2.537	0.665	0.566	0.633		
Training and Development (TD)	TD1 TD2 TD3 TD4 TD5	0.881	0.913	0.677	0.793 0.844 0.827 0.824 0.827	1.864 2.352 2.177 2.069 2.238	0.648	0.583	0.596	0.461	

Table 3. Hypotheses testing and f-square and R-squared values.

Hypothesis	Path	f^2	β	T-Statistics	*p*-Value	Result
H1	KS → EE	0.118	0.260	3.705	0.000	Accepted
H2	EM → EE	0.424	0.475	6.312	0.000	Accepted
H3	TD → EE	0.047	0.131	2.827	0.005	Accepted
H4	PE → EE	0.070	0.164	2.723	0.007	Accepted
Endogenous Variable		**R^2**		**R^2 Adjusted**		
EE		0.758		0.753		

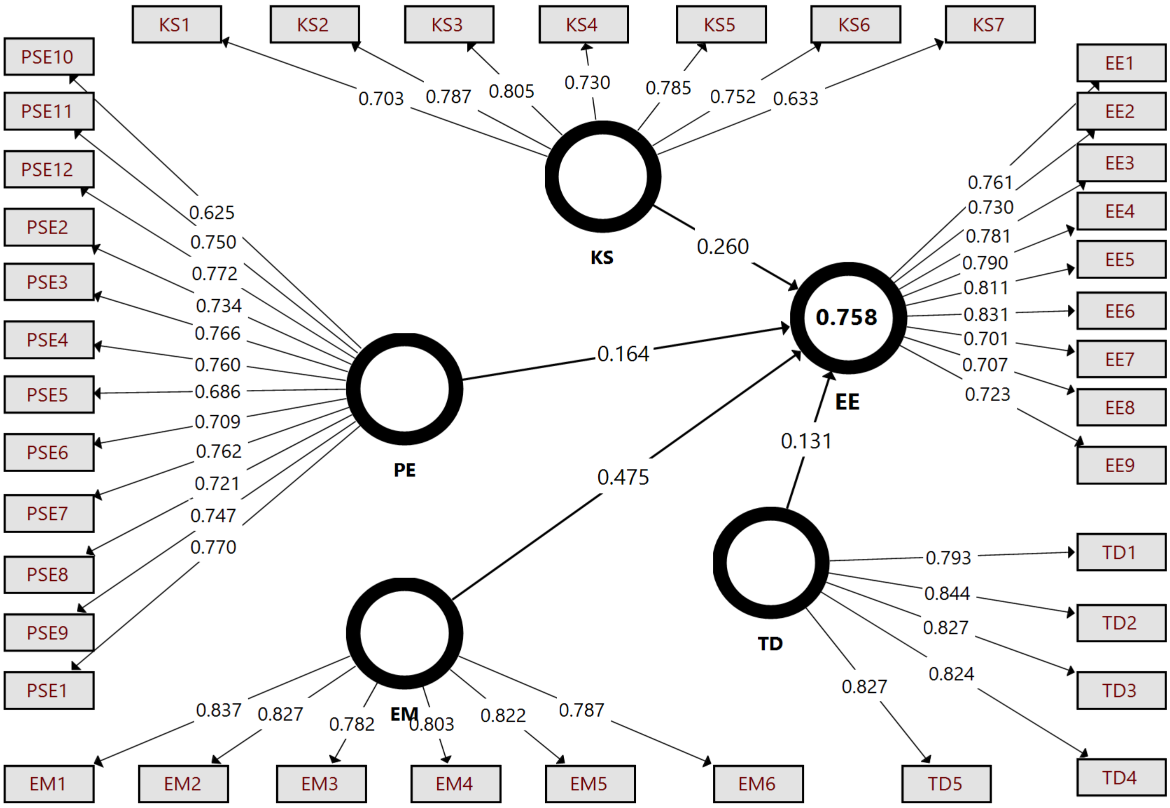

Figure 2. PLS-SEM model.

4.4. PLSpredict

We applied PLSpredict, a cross-validation technique (k-fold cross-validation), to assess the strength of the model's predictive power. In PLS-SEM, such a cross-validation technique is typically shown as ten folds and ten repetitions [75]. Regarding the interpretation of PLSpredict outcomes, this does not necessitate assessing the prediction errors for each response variable. In contrast, the initial focus involves evaluating the prediction errors for the PLS path model's primary endogenous variable. In PLSpredict, the Q^2_ prediction indicates whether the predictions are greater than the naïve benchmark criterion. If prediction outcomes are shown as Q^2 values > 0 (better than the naïve benchmark criterion), then an assessment of further prediction statistics is required [76]. In PLSpredict analysis, Shmueli et al. [77] suggested the criteria to choose between root mean square error (RMSE) and mean absolute error (MAE) benchmarks by examining the indicators' prediction error terms. The indicator's prediction attained by comparing the PLS model is then used in comparing those found values with the linear model (LM) model and the simple mean (Q^2_predict) for each indicator of endogenous variable as a means of benchmarking. Table 4 shows that all the indicators' Q^2-predict values were above 0 in this study, confirming the models' predictive power. This study calculated the partial least squares prediction (PLSpredict) method to show the predictive validity of the PLS path models. Compared to a linear regression model (LM), partial least squares structural equation modeling (PLS-SEM) utilizes a theoretically established path model to make predictions. The LM approach, on the other hand, generates predictions by regressing exogenous indicator variables on each endogenous indicator variable. A comparison of the prediction errors between the two methods (e.g., root mean squared error (RMSE) or mean absolute error (MAE)) can provide insights into the added value of using a theoretically established path model in PLS-SEM. If the PLS-SEM results have a lower prediction error compared to the LM approach, it suggests that the path model improves the predictive performance of the available indicator data. However, it is essential to note that the LM prediction error is only available for manifest variables, not latent ones. It was found that root means squared error (RMSE) and mean absolute error (MAE) values of the PLS model are lower than linear regression model (LM) sections, whilst Q^2 values are greater than LM's respective values, which indicates a considerably higher predictive power for the proposed model with non-overfitting problems.

Table 4. PLSpredict.

Items	PLS			LM			PLS-LM		
	RMSE	MAE	Q^2_predict	RMSE	MAE	Q^2_predict	RMSE	MAE	Q^2_predict
EE1	0.551	0.445	0.391	0.6	0.477	0.278	−0.049	−0.032	0.113
EE2	0.579	0.44	0.387	0.617	0.481	0.304	−0.038	−0.041	0.083
EE3	0.555	0.446	0.431	0.599	0.479	0.337	−0.044	−0.033	0.094
EE4	0.565	0.46	0.437	0.604	0.479	0.355	−0.039	−0.019	0.082
EE5	0.583	0.462	0.421	0.635	0.507	0.314	−0.052	−0.045	0.107
EE6	0.561	0.458	0.483	0.604	0.481	0.401	−0.043	−0.023	0.082
EE7	0.627	0.504	0.411	0.691	0.534	0.284	−0.064	−0.03	0.127
EE8	0.611	0.514	0.398	0.677	0.556	0.261	−0.066	−0.042	0.137
EE9	0.603	0.498	0.443	0.648	0.524	0.358	−0.045	−0.026	0.085

4.5. Multigroup Analysis

The present study utilized the partial least squares (PLS) structural modeling technique to conduct a multigroup analysis. PLS multigroup analysis aims to determine whether there are significant differences in the PLS model between groups, as stated by Cheah et al. [78]. The author further elucidated the concept of multigroup analysis by utilizing independent sample t-tests to compare the paths between different groups, as discussed in [79,80]. Given the diversity of groups represented in the study, evaluating the distinctions between these departments is essential. Table 5 presents the results of a multigroup analysis conducted on five departments: IT, admission, HR, finance, and marketing. The study designates the IT department as the benchmark for proficiency and responsiveness in digital transformation initiatives, and thus it was selected as the base department. The statistics generated from parametric and Welch-Satterthwaite tests indicate a significant difference between the knowledge sharing and employee engagement association in the IT and admission departments, with the latter performing better in these areas, which shows that the knowledge sharing factor intrigues the job engagement aspect in admission department employees to a higher degree than in the IT department. However, no significant differences were found between these two departments for the remaining hypotheses. In contrast, the analysis revealed a significant difference in the employee mobility and engagement path between the IT and finance departments, suggesting that the employee mobility factor may contribute to higher levels of engagement among finance department employees compared to the IT department. The study also found that the IT department outperforms the HR department in all variables and their associations, with no significant differences observed for any hypotheses. Lastly, the research discovered a significant difference in the association of employee mobility with employee engagement between the IT and marketing departments, indicating that promoting engagement through employee mobility practices may be more effective in the marketing department than in the IT department. However, no significant differences were found between the two departments for the remaining variables or their associations.

Table 5. Multigroup analysis.

IT–Admission	Path Coefficients-Diff (IT-Admission)	*p*-Value Original 1-Tailed (IT vs. Admission)	*p*-Value New (IT vs. Admission)	*p*-Value (Parametric Test)	*p*-Value (Welch-Satterthwait Test)
EM → EE	0.201	0.071	0.071	0.080	0.067
KS → EE	**−0.311**	**0.995**	**0.005**	**0.008**	**0.005**
PE → EE	−0.050	0.649	0.351	0.371	0.360
TD → EE	0.052	0.327	0.327	0.331	0.329
IT–Finance	**Path Coefficients-diff (IT-Finance)**	***p*-Value Original 1-tailed (IT vs. Finance)**	***p*-Value New (IT vs. Finance)**	***p*-Value (Parametric Test)**	***p*-Value (Welch-Satterthwait Test)**
EM → EE	**0.500**	**0.011**	**0.011**	**0.008**	**0.019**
KS → EE	−0.263	0.905	0.095	0.070	0.085
PE → EE	−0.180	0.868	0.132	0.164	0.134
TD → EE	−0.189	0.947	0.053	0.075	0.057
IT–HR	**Path Coefficients-diff (IT-HR)**	***p*-Value Original 1-Tailed (IT vs. HR)**	***p*-Value New (IT vs. HR)**	***p*-Value (Parametric Test)**	***p*-Value (Welch-Satterthwait Test)**
EM → EE	−0.001	0.502	0.498	0.499	0.498
KS → EE	−0.182	0.880	0.120	0.171	0.125
PE → EE	0.024	0.420	0.420	0.457	0.444
TD → EE	0.070	0.293	0.293	0.330	0.294
IT–Marketing	**Path Coefficients-diff (IT-Marketing)**	***p*-Value Original 1-Tailed (IT vs. Marketing)**	***p*-Value New (IT vs. Marketing)**	***p*-Value (Parametric Test)**	***p*-Value (Welch-Satterthwait Test)**
EM → EE	**0.548**	**0.033**	**0.033**	**0.012**	**0.025**
KS → EE	−0.388	0.839	0.161	0.072	0.167
PE → EE	−0.237	0.778	0.222	0.178	0.208
TD → EE	0.023	0.440	0.440	0.449	0.452

4.6. IPMA

Importance-performance map analysis (IPMA) can be used in the context of employee engagement in digital transformation to identify the most important factors that drive employee engagement and evaluate the performance of different initiatives to increase employee engagement. In this context, IPMA can be used to visualize the relationship between the importance of model factors (employee mobility, knowledge sharing, psychological empowerment, and training and development) and their perceived performance by employees. It plots the importance of each factor on the *x*-axis and the performance of each factor on the *y*-axis. Factors that are located in the upper right quadrant of the map are considered to be the most important and performing well, while those in the lower left quadrant are considered to be the least important and performing poorly. Using IPMA, organizations can identify the key drivers of employee engagement and prioritize initiatives that address those factors. It can also help to evaluate the effectiveness of current engagement strategies and identify areas for improvement. Overall, IPMA can be a valuable tool for organizations to understand the factors influencing employee engagement in digital transformation and improving employee engagement.

For this study, the IPMA test results for the collected sample, as depicted in Figure 3 and Table 6, showed that employee mobility (EM) lies in Q2, psychological empowerment (PE) lies in Q3, and knowledge sharing (KS) and training and development (TD) land in Q4. Moreover, IPMAs for each department were also calculated to comprehend the significance of model variables in each department, as shown in Table 6.

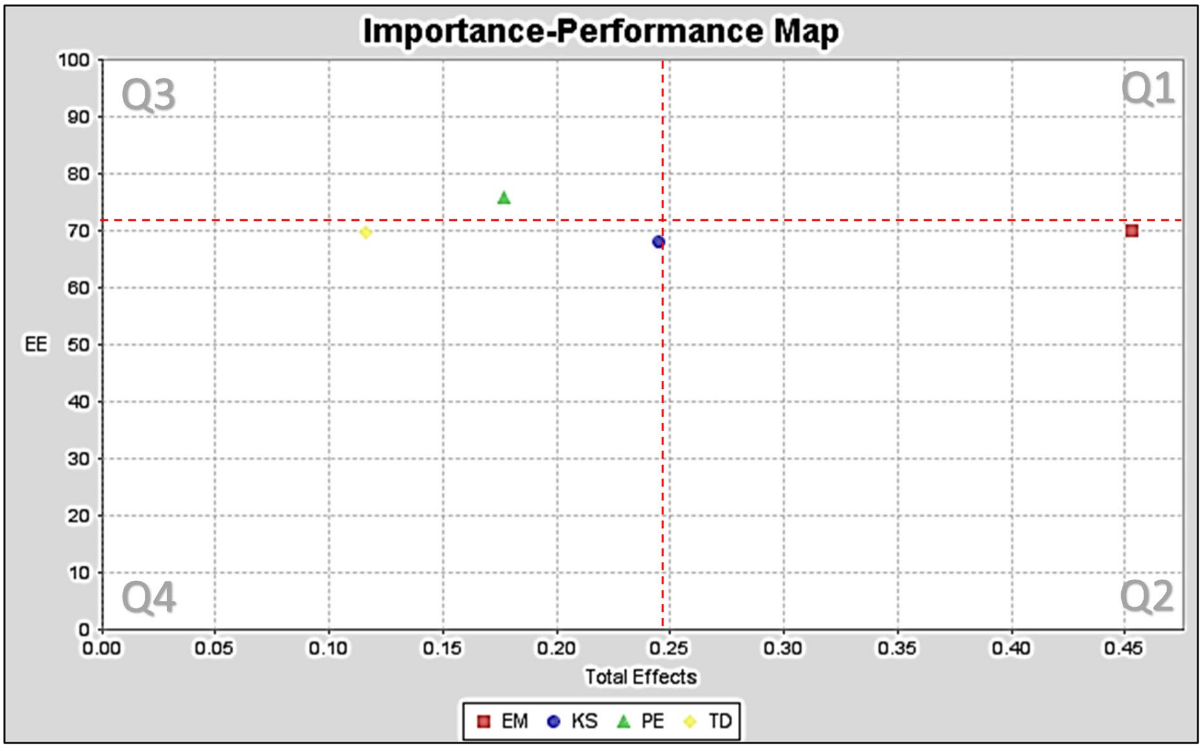

Figure 3. IPMA for all departments.

Table 6. IPMA for all data sample and for each department.

Particulars	IPMA Factors	EM	KS	PE	TD	Average Values
All Departments	Importance	0.4525	0.2450	0.1768	0.1159	0.2475
	Performances	70.082	67.924	75.837	69.827	70.9173
	Placement	Q2	Q4	Q3	Q4	
IT	Importance	0.593	0.067	0.114	0.120	0.223
	Performances	68.731	67.079	76.146	67.811	69.942
	Placement	Q2	Q4	Q3	Q4	
Admission	Importance	0.391	0.381	0.172	0.114	0.265
	Performances	73.954	69.142	78.799	72.311	73.552
	Placement	Q1	Q2	Q3	Q4	
Finance	Importance	0.142	0.307	0.346	0.363	0.289
	Performances	70.685	68.377	75.991	74.229	72.320
	Placement	Q4	Q2	Q1	Q1	
HR	Importance	0.610	0.239	0.083	0.079	0.253
	Performances	66.808	68.620	73.977	67.193	69.149
	Placement	Q2	Q4	Q3	Q4	
Marketing	Importance	0.073	0.414	0.316	0.114	0.229
	Performances	67.308	64.901	68.591	68.373	67.293
	Placement	Q3	Q2	Q1	Q4	

5. Discussion and Implications

The purpose of this research was to shed light on the impact of significant elements, such as knowledge sharing (KS), employee mobility (EM), training and development (TD), and psychological empowerment (PE), on cultivating employee engagement (EE) within the context of workplace transformation driven by modern technologies. Following the analysis of survey responses from 205 non-academic professionals working in the Malaysian higher education sector, our results were based on PLS-SEM analysis, used to test the hypotheses and validate the theoretical model; multigroup analysis (MGA), used to compare the level of significance of model variable on the basis of departments; and importance-performance map analysis (IPMA), used to assess the overall model position, as well as that of the individual departments. Before PLS-SEM analysis, data were assessed for biasness using the CMB technique. After conducting the PLS-SEM analysis, the model was validated for its prediction relevance through the blindfolding process. Later on, to assess the strength of the model prediction power, the PLS-predict technique was also applied and validated.

PLS-SEM results indicated that KS, EM, TD, and PE were jointly constructed to explain the 76% change in EE. More specifically, each hypothesis, i.e., H1 (KS → EE), H2 (EM → EE), H3 (TD → EE), and H4 (PE → EE), was supported with a significance level of <0.05. These findings confirm and support prior research conclusions regarding the proposed structural relationship in our model [27,28,33,39,40,60]. On the other hand, among the four hypotheses, H1 and H2 are robustly supported by the regression path of KS (26%) and EM (48%) towards EE; thus, KS and EM seem to be more influential factors in increasing EE. This shows that organizations should find ways for the employee mobility factor to strengthen EE effectively.

Our analyses reconfirmed prior views that TD and PE positively change employee engagement in the same direction [34,40,43,61]. According to ICTC [49], TD accelerates "21st-century learning environments" to reduce the tech skills gap, resulting in higher-skilled employees, in which the difficulty of engaging workforces for the modern workplace can be irresistible. As today's organizations are facing several changes through digital transformation, psychologically empowered workers are much more crucial in triggering those changes [81–83]. Consistently, we found that TD and PE enhance EE in these days of modern organizations. These findings may benefit higher education institutions by promoting a positive organizational culture and improving employee engagement. This, in turn, can lead to increased operational efficiency in digital transformation and provide a competitive advantage. However, TD and PE have comparatively less impact among the modelled variables towards EE. Reliance on these two variables, while ignoring two key variables (i.e., KS and EM), may not robustly achieve the desired engagement levels among staff in a technology-driven working environment.

By developing their information technology strategies, several firms—for example, higher education institutions—are well prepared to shift to the digital workplace, known by a new term: "born-digital" organizations [84]. KS and EM are key trends [25,30,33]. Likewise, technological innovations develop the knowledge and actions of employees in an organization in a practical setting [85]. This is why innovative socio-technical systems, and new norms and behaviors are assessed in an organization with technological transformation [40]. Therefore, KS among the employees stimulates them to learn and perform together at the organization [86], resulting in sustainable EE [27,28,65].

To assess the robustness of crafting EE predictors, the MGA and IPMA were tested for each department. Understanding the role of the model in each department within a university is crucial for comprehending differences, providing targeted support, effectively allocating resources, and making informed decisions. It helps identify leading departments, support struggling ones, allocate resources, and make evidence-based decisions for digital transformation initiatives. In this sense, the MGA result explains inferences about departments, as the KS role has more influence on EE in the admission department than the IT department. This means that the practice of knowledge sharing was found to have a more significant impact on enhancing employee engagement levels in the admission department compared to the IT department in universities. This suggests that the admission department may benefit more from implementing effective knowledge-sharing initiatives and practices than the IT department. Moreover, the role of employee mobility (EM) in engaging employees in the finance and HR departments is significantly varied. This could be due to differences in departmental goals, work processes, job responsibilities, and employee motivation, among other factors. In the finance and marketing departments, increased employee mobility may increase exposure to new ideas, diverse perspectives, and opportunities, leading to higher engagement. To justify this result, further research could be conducted to understand the underlying reasons for this impact difference and identify best practices for managing employee mobility in each department to enhance engagement levels.

By expanding the sturdiness of analysis, the IPMA results for all departments explained that EM lies in Q2 (with higher importance and lower performance), suggesting that all stakeholders should pay attention to this factor. Table 6 shows that the IT and HR departments need to pay more attention to improving employee mobility practices, towards engaging the employees. There are various ways to increase employee mobility in IT and HR departments, including flexible work arrangements, job rotation programs, cross-functional collaboration, training and development opportunities, and employee recognition and rewards. Offering flexible work arrangements such as working from home or flexible hours can reduce commuting time and increase employee mobility. Implementing job rotation programs allows employees to gain new experiences and skills, leading to growth opportunities. Encouraging cross-functional collaboration and providing training and development programs can broaden employees' skills and knowledge. Recognizing and rewarding employees for their contributions can also increase employee engagement and motivation. These measures can help improve employee mobility and drive engagement in the IT and HR departments. While knowledge sharing for the admission, marketing, and finance departments lie in the Q2 quadrant, revealing their lower level of performance with higher importance, ultimately calls for focus and ponderance. Enhancing knowledge sharing in the marketing, admission, and finance departments can be achieved through several strategies; for example, creating a collaborative work environment, where team members work together in shared spaces, is one way to increase cross-functional collaboration. Implementing mentorship programs can offer employees opportunities to learn from experienced colleagues. A knowledge management system can help to store, organize, and share information and best practices. Encouraging employees to share their knowledge through presentations, workshops, or other forms of training and development can help spread information throughout the departments. Incentives, such as bonuses or recognition programs, can be offered to employees who share their knowledge. Open communication channels, such as suggestion boxes or regular meetings, facilitate the sharing of information and ideas. Finally, cross-departmental projects can bring employees from different departments together, promoting knowledge sharing across the organization.

Relatedly, as digital transformation is rapidly reshaping most business firms [24], a sense of urgency regarding employee connectedness has become crucial for the current organizational change [87]. Therefore, current employers are keenly aware of interpreting those factors that may influence EE in the digital workplace, such as cognitive-based encouragement, transferring knowledge, agile workforces, and training and development [27,31,36,88]. Although higher education institutions have been found to be more flexible in adopting KS and EM practices compared to other sectors [27,66,89], the digital workplace is not limited to a single sector and is becoming increasingly prevalent across all industries. In this context, "technological innovation" involves better reflecting advancements in other professionals, such as academicians, corporate trainers, IT professionals, and clerical and administrative staff. The impact of COVID-19 has also urged many organizations towards digital workplace trends, in which KS and EM may be dynamically embraced as the new normal. Working from home and the sharing of knowledge occur genuinely due to this pandemic, which brings individuals, team members, and opinions together. The findings of our research are also consistent with these views. We thus recommend that not only higher education institutions but also other sectors bear KS and EM in mind more specifically for making sustainable EE goals. Indeed, HR managers, business leaders, and academics may benefit from these research findings for better understanding and to substantiate the perceived impacts of KS and EM on EE in the digital workplace.

Social exchange theory (SET) is a sociological perspective that views social behavior as the outcome of a reciprocal exchange process between individuals. According to Chernyak-Hai and Rabenu [21], SET provides valuable insight into the exchange relationship between employees and companies in today's digital workplaces. Our findings in this study confirm the validity of SET in promoting employee engagement. Organizations can create a positive and reciprocal relationship by adopting practices such as implementing a knowledge sharing platform, embracing remote work culture, providing training and development opportunities, and promoting psychological empowerment among employees. Employees who perceive that their companies are concerned about their wellbeing and growth become more engaged in and dedicated to their work. The mutual action between the company and employees fosters a work environment where both parties benefit. This, in turn, leads to increased employee satisfaction, motivation, and overall productivity. Therefore, organizations need to understand the significance of SET and adopt practices that promote a positive exchange relationship between employees and their company [17,22,23,67].

From an academic viewpoint, this study is among the first attempts to illustrate the relationship between certain factors (i.e., KS, EM, TD, and PE) and EE in the digital workplace context. Earlier research on the impact of these factors on employees' positive behavioral outcomes was conducted with limited scope, particularly in a non-digital workspace scenarios [27,31,33,40,65]. Thus, the findings of this study undoubtedly represent a novel contribution to the existing academic literature to reshape EE in sustainability. In addition, our study has potency in aiding understanding of "Sustainable Development Goal 9 (SDG-9)", i.e., reliable, workable and resilient infrastructures, including human resources and innovation management [90].

6. Limitations and Recommendations

This paper contains some limitations and recommendations for further study. Firstly, this study involved collecting data at one point, which does not provide enough opportunities to check a causal effect between two timespans [81]. Hence, a longitudinal research design might be preferable for future research attempting to demonstrate robust cause–effect relationships. Secondly, this research focused on academic sector employees; therefore, further study regarding new insights into different sector contexts can be carried out to enhance the generalizability of the results. Furthermore, the literature review provides evidence of the inadequacy of qualitative study in this area; in the future, qualitative research work should therefore be studied. Interviewing target respondents might be suitable to sightsee the factors deterring workers from using organizational resources [91]. Another aspect of this study that needs future improvement is related to the data collection sampling. It is important to note that convenience sampling was the most feasible approach to reach the desired sample size due to physical restrictions and limitations in randomly selecting participants during the COVID-19 pandemic. While this approach may have limitations, we took steps to mitigate the potential biases by conducting a common method bias test. However, we acknowledge the importance of using representative sampling methods such as stratified or systematic random sampling in future studies to increase the generalizability of the findings. Lastly, we only considered KS, EM, TD, and PE as relevant EE precursors in the organization's digital transformation context. Thus, other factors—for instance, digital competency, workplace ergonomics, workplace flexibility, and collaborative work—can be addressed as engagement strategies in any further research on tech-oriented workplace scenario contexts.

7. Conclusions

Employee engagement (EE) entails precursors in an organization that stimulates the workforce to be dedicated and committed to their job responsibilities. In prioritizing EE, technology-oriented organizations can turn their attention to knowledge sharing (KS), employee mobility (EM), training and development (TD), and psychological empowerment (PE) to keep workers motivated and energetic. By emphasizing this scenario, we have shed light on the impact of such influential factors on EE in digital workplace mechanisms. Based on responses from employees at different universities in Klang Valley, we found that KS, EM, TD, and PE can stir workforces to be emotionally and physically connected at work. To strengthen EE strategies in the academic sector and possibly other organizations, we recommend that HR leaders focus on sustaining employee engagement instead of assessing their job duties. In essence, all employers require better employee engagement (EE), and the means to achieve this is lie in fostering a higher level of engagement among employees. If employees are happier and more satisfied with organizational strategy, it will lead to better outcomes. Such a strategy may provide workers with opportunities for what they want from the organization, resulting in higher engagement levels. Therefore, KS, EM, TD, and PE should be considered in the planning phase of EE strategies that will support HR managers in keeping sustainable EE. Once they have attained truly engaged employees, technological change in the organization may become unconfined to improve organizational effectiveness and employee retention. It is where the business firms are steered, and it is where they want to reach.

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Appendix A

Questionnaire Items

	Knowledge Sharing (KS)
KS1	I often share new working skills with my colleagues.
KS2	Our colleagues often share the new working skills that they learn.
KS3	Sharing knowledge with colleagues is regarded as something normal.
KS4	Our colleagues often share their work experiences.
KS5	I often share my job experiences with colleagues when they ask.
KS6	Our organization's staff often exchanges knowledge of working skills and information.
KS7	Our colleagues often share the new information that they acquire.
	Employee Mobility (EM)
EM1	My organization prioritizes the movement of its potential employees.
EM2	My organization has a clearly articulated employee mobility process.
EM3	My organization allows for vertical moves (taking a higher-level role).
EM4	My organization allows for lateral moves (taking on a new role at the same level).
EM5	My organization has a relocation policy (moving to another geographical office).
EM6	My organization has enrichment activities (growing in place—e.g., taking on new assignments/tasks).

Training and Development (TD)	
TD1	Our company spends enough money and time on related training programs.
TD2	Within my organization, I receive training to develop my problem-solving skills.
TD3	Within my organization, leadership skills development training is provided.
TD4	With training, I am skillful in understanding the organizational work policy.
TD5	Through training, I am able to make any group decision.
Psychological Empowerment (PE)	
PE1	The work I do is very important to me.
PE2	My job activities are personally meaningful to me.
PE3	The work I do is meaningful to me.
PE4	I am confident about my ability to do my job.
PE5	I am self-assured about my capabilities to perform my work activities.
PE6	I have mastered the skills necessary for my job.
PE7	I have significant autonomy in determining how I do my job.
PE8	I can decide on my own how to go about doing my work.
PE9	I have considerable opportunities for independence and freedom in how I do my job.
PE10	My impact on what happens in my department is large.
PE11	I have a great deal of control over what happens in my department.
PE12	I have significant influence over what happens in my department.
Employee Engagement (EE)	
EE1	At work, I am bursting with energy.
EE2	At my job, I feel strong and vigorous.
EE3	I am enthusiastic about my job.
EE4	My job inspires me.
EE5	When I get up in the morning, I feel like going to work.
EE6	I feel happy when I am working intensely.
EE7	I am proud of the work that I do.
EE8	I am immersed in my work.
EE9	I get carried away when I am working

References

1. Meske, C.; Junglas, I. Investigating the elicitation of employees' support towards digital workplace transformation. *Behav. Inf. Technol.* **2020**, *40*, 1120–1136. [CrossRef]
2. Ahmed, W.; Hizam, S.M.; Sentosa, I. Digital Dexterity: Employee as Consumer Approach towards Organizational Success. *Hum. Resour. Dev. Int.* **2020**, *25*, 631–641. [CrossRef]
3. Singh, A.; Hess, T. How chief digital officers promote the digital transformation of their companies. *MIS Q. Exec.* **2017**, *16*, 1–17. [CrossRef]
4. Gartner. *Executive Guidance: Digital Dexterity at Work*; Gartner: Stamford, CT, USA, 2018; pp. 1–29. Available online: https://www.gartner.com/en/executive-guidance/digital-dexterity (accessed on 9 February 2023).
5. Saran, C. Study Reveals Employees' Fears over Digital Change. 2017. Available online: https://www.computerweekly.com/news/450429100/Study-reveals-employees-fears-over-digital-change (accessed on 9 February 2023).
6. Mittal, R.; Pankaj, P.; Aggarwal, S.; Kaul, A. Evaluation of Adoption of Blockchain Technology for Supply Chain Management: A Case of Indian MSME. In *Soft Computing for Problem Solving*; Springer: Singapore, 2021; pp. 621–633.
7. Winasis, S.; Djumarno; Riyanto, S.; Ariyanto, E. Digital Transformation in the Indonesian Banking Industry: Impact on Employee Engagement. *Int. J. Innov. Creat. Chang.* **2020**, *12*, 528–543.
8. Vardarlier, P.; Ozsahin, M. Digital Transformation of Human Resource Management: Social Media's Performance Effect. *Int. J. Innov. Technol. Manag.* **2021**, *18*, 2150005. [CrossRef]
9. Ulas, D. Digital Transformation Process and SMEs. *Procedia Comput. Sci.* **2019**, *158*, 662–671. [CrossRef]
10. Katiliūtė, E.; Stankevičiūtė, Ž.; Daunorienė, A. The Role of Non-academic Staff in Designing the Green University Campus. In *Handbook of Theory and Practice of Sustainable Development in Higher Education*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 49–61.
11. Mugizi, W.; Odetha Katuramu, A.; Ogaga Dafiewhare, A.; Kanyesigye, J. Rewards and Work Engagement of Non-Academic Staff: A Case of a Public University in Uganda. *East Afr. J. Educ. Soc. Sci.* **2020**, *1*, 79–88. [CrossRef]
12. Baltaru, R.-D. Do non-academic professionals enhance universities' performance? Reputation vs. organisation. *Stud. High. Educ.* **2019**, *44*, 1183–1196. [CrossRef]

13. Nkechi, P.A.J.; Dialoke, I. Effects of Career Growth on Employees Performance: A Study of Non-Academic Staff of Michael Okpara University of Agriculture Umudike Abia State, Nigeria. *World J. Entrep. Dev. Stud.* **2017**, *5*, 8–18. [CrossRef]
14. Alias, N.E. Employee Satisfaction in Higher Education: A Malaysian Case Study among Non-Academic Staff. *Acad. J. Bus. Soc. Sci.* **2017**, *1*, 1–14. Available online: http://ir.uitm.edu.my/id/eprint/29964/ (accessed on 9 February 2023).
15. Nasidi, Y.; Makera, A.U.; Kamaruddeen, A.M.; Jemaku, I.M. Assessing the Impact of Work Environment on Employee Engagement among Non-Academic Staff of the University. *SEISENSE J. Manag.* **2019**, *2*, 57–68. [CrossRef]
16. Juan, S.H.; Yao, L.; Tamyez, P.F.B.M.; Ayodele, F.O. Review on Knowledge Management and Employee Engagement. In Proceedings of the National Conference for Postgraduate Research 2016, Pahang, Malaysia, 24–25 September 2016; pp. 127–134.
17. Garfield, S. Employee Engagement in the Digital Workplace. In Proceedings of the Uropean SharePoint, Office 365 & Azure Conference, Prague, Czech Republic, 18 November 2016.
18. Tran, K. *Maximising Employee Training and Development in the Digital Workplace*; TRG International: Ho Chi Minh City, Vietnam, 2018.
19. Hamburg, I. Implementation of a Digital Workplace Strategy to Drive Behavior Change and Improve Competencies. In *Strategy and Behaviors in the Digital Economy*; Orlando, B., Ed.; IntechOpen: London, UK, 2019; pp. 1–16.
20. Aldabbas, H.; Pinnington, A.; Lahrech, A. The mediating role of psychological empowerment in the relationship between knowledge sharing and innovative work behaviour. *Int. J. Innov. Manag.* **2020**, *25*, 21500146. [CrossRef]
21. Chernyak-Hai, L.; Rabenu, E. The New Era Workplace Relationships: Is Social Exchange Theory Still Relevant? *Ind. Organ. Psychol.* **2018**, *11*, 456–481. [CrossRef]
22. Olubunmi, F.; Samuel, O.; Babalola, O. Factors influencing knowledge sharing among information and communication technology artisans in Nigeria. *J. Syst. Inf. Technol.* **2016**, *18*, 148–169. [CrossRef]
23. Rehman, W.U.; Ahmad, M.; Allen, M.M.C.; Raziq, M.M.; Riaz, A. High involvement HR systems and innovative work behaviour: The mediating role of psychological empowerment, and the moderating roles of manager and co-worker support. *Eur. J. Work Organ. Psychol.* **2019**, *28*, 525–535. [CrossRef]
24. Attaran, M.; Attaran, S.; Kirkland, D. The need for digital workplace: Increasing workforce productivity in the information age. *Int. J. Enterp. Inf. Syst.* **2019**, *15*, 1–23. [CrossRef]
25. Dery, K.; Sebastian, I.M.; Meulen, N. van der The digital workplace is key to digital innovation. *MIS Q. Exec.* **2017**, *16*, 135–152.
26. Rahman, M.S.; Daud, N.M.; Hassan, H. Generation "X" and "Y" knowledge sharing behaviour: The influence of motivation and intention on non-academic staff of higher learning institutions. *J. Appl. Res. High. Educ.* **2017**, *9*, 325–342. [CrossRef]
27. Eccarius, T.; Lu, C.C. Adoption intentions for micro-mobility—Insights from electric scooter sharing in Taiwan. *Transp. Res. Part D Transp. Environ.* **2020**, *84*, 102327. [CrossRef]
28. Ahmed, W. Understanding self-directed learning behavior towards digital competence among business research students: SEM-neural analysis. *Educ. Inf. Technol.* **2022**. [CrossRef]
29. Saks, A.M. Antecedents and consequence of work engagement. *J. Manag. Psychol.* **2006**, *21*, 600–619. [CrossRef]
30. Koon, V.Y.; Chong, K.N. Workplace flexibility and organisational citizenship behaviour: An investigation of the mediating role of engagement and moderating role of perceived fairness. *Int. J. Work. Organ. Emot.* **2018**, *9*, 45–62. [CrossRef]
31. Lai, P.; Lee, J.; Lim, Y.; Yeoh, R.; Mohsin, F.H. The Linkage between Training and Development and Co-Worker Support towards Employee Engagement in Hotel Industry. *Int. J. Sci. Res. Publ.* **2015**, *5*, 1–8.
32. Maan, A.T.; Abid, G.; Butt, T.H.; Ashfaq, F.; Ahmed, S. Perceived organizational support and job satisfaction: A moderated mediation model of proactive personality and psychological empowerment. *Future Bus. J.* **2020**, *6*, 21. [CrossRef]
33. Cropanzano, R.; Anthony, E.L.; Daniels, S.R.; Hall, A.V. Social Exchange Theory: A Critical Review with Theoretical Remedies. *Acad. Manag. Ann.* **2017**, *11*, 479–516. [CrossRef]
34. Wu, W.-L.; Lee, Y.-C. Empowering group leaders encourages knowledge sharing: Integrating the social exchange theory and positive organizational behavior perspective. *J. Knowl. Manag.* **2017**, *21*, 474–491. [CrossRef]
35. Aktar, A.; Pangil, F. Mediating role of organizational commitment in the relationship between human resource management practices and employee engagement: Does black box stage exist? *Int. J. Sociol. Soc. Policy* **2018**, *38*, 606–636. [CrossRef]
36. Göçer, Ö.; Göçer, K.; Karahan, E.E.; Oygür, I.İ. Exploring mobility & workplace choice in a flexible office through post-occupancy evaluation. *Ergonomics* **2018**, *61*, 226–242. [CrossRef]
37. Arefin, M.S.; Alam, M.S.; Islam, M.R.; Rahaman, M. High-performance work systems and job engagement: The mediating role of psychological empowerment. *Cogent Bus. Manag.* **2019**, *6*, 1664204. [CrossRef]
38. Meira, J.V.d.S.; Hancer, M. Using the social exchange theory to explore the employee- organization relationship in the hospitality industry. *Int. J. Contemp. Hosp. Manag.* **2021**, *33*, 670–692. [CrossRef]
39. Ahmad, F. Knowledge sharing in a non-native language context: Challenges and strategies. *J. Inf. Sci.* **2018**, *44*, 248–264. [CrossRef]
40. Li, J.; Herd, A.M. Shifting practices in digital workplace learning: An integrated approach to learning, knowledge management, and knowledge sharing. *Hum. Resour. Dev. Int.* **2017**, *20*, 185–193. [CrossRef]
41. Juan, S.H.; Ting, I.W.K.; Kweh, Q.L.; Yao, L. How does knowledge sharing affect employee engagement? *Inst. Econ.* **2018**, *10*, 49–67.
42. Al-Jabri, I.M. Investigating the mediating role of knowledge sharing on employee engagement: Evidence from a developing nation. *Int. J. Hum. Cap. Inf. Technol. Prof.* **2020**, *11*, 47–63. [CrossRef]
43. Shah, M. *Employee Mobility: Is It Beneficial for Your Business*; TechFunnel: Frisco, TX, USA, 2018.

44. Rajagopal, A. Relationship between Employee Mobility and Organizational Creativity to Improve Organizational Performance: A Strategic Analysis. In *Business Governance and Society*; Rajagopal, B.R., Ed.; Palgrave Macmillan: Cham, Switzerland, 2019; pp. 237–250.
45. De Kok, A.; Lubbers, Y.; Helms, R.W. Mobility and security in the new way of working: Employee satisfaction in a Choose Your Own Device (CYOD) environment. In Proceedings of the Ninth Mediterranean Conference on Information Systems (MCIS), Samos, Greece, 2–5 October 2015; pp. 1–20.
46. Edwards, R.G. *How Mobile Technology is Transforming Workplace Performance How Mobile Technology is Transfoming Workplace Performance*; Nudge Rewards Inc.: Toronto, ON, Canada, 2017.
47. Azeem, M.F.; Rubina; Paracha, A.T. Connecting training and development with employee engagement: How does it matter? *World Appl. Sci. J.* **2013**, *28*, 696–703. [CrossRef]
48. DeCenzo, D.A.; Robbins, S.P.; Verhulst, S.L. *Human Resource Management*, 11th ed.; International Student Version; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2013.
49. ICTC. *Digital Talent Road to 2020 and Beyond: A National Strategy to Develop Canada's Talent in a Global Digital Economy*; ICTC: Muskogee, OK, USA, 2016.
50. Golubenko, S. How Digital Transformation Refashions Employee Training and Development. 2018. Available online: https://www.scnsoft.com/blog/digital-transformation-of-employee-training-development (accessed on 9 February 2023).
51. Khan, A.J.; Iqbal, J. Training and Employee Commitment: The Social Exchange Perspective. *J. Manag. Sci.* **2020**, *7*, 88–100. [CrossRef]
52. Spreitzer, G.M. Psychological empowerment in the workplace: Dimensions, measurement, and validation. *Acad. Manag. J.* **1995**, *38*, 1442–1465. [CrossRef]
53. Meng, Q.; Sun, F. The impact of psychological empowerment on work engagement among university faculty members in China. *Psychol. Res. Behav. Manag.* **2019**, *12*, 983–990. [CrossRef]
54. Owan, V.J.; Bassey, B.A.; Mbon, U.F.; Okon, A.E.; Egbula, E.O.; Ekaette, S.O.; Ojong, C.O.; Ekpe, M.B. Validation of an Instrument and Measurement of Employee Work-Life Policies, Psychological Empowerment, and Job Commitment of Academic Staff in Universities. *Mediterr. J. Soc. Sci.* **2020**, *11*, 86–100. [CrossRef]
55. Helmy, I.; Adawiyah, W.R.; Banani, A. Linking Psychological Empowerment, Knowledge Sharing, and Employees' Innovative Behavior in SMEs. *J. Behav. Sci.* **2019**, *14*, 66–79.
56. Saunders, M.N.K.; Lewis, P.; Thornhill, A. *Research Methods for Business Students*, 8th ed.; Pearson: London, UK, 2019.
57. Stratton, S.J. Population Research: Convenience Sampling Strategies. *Prehosp. Disaster Med.* **2021**, *36*, 373–374. [CrossRef] [PubMed]
58. Sekaran, U.; Bougie, R. *Research Methods for Business: A Skill Building Approach*, 7th ed.; Wiley: New York, NY, USA, 2016.
59. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 3rd ed.; The Guilford Press: New York, NY, USA, 2011.
60. i4cp. *2015 Talent Mobility Survey*; i4cp: Washington, DC, USA, 2015.
61. Edgar, F.; Geare, A. HRM practice and employee attitudes: Different measures—Different results. *Pers. Rev.* **2005**, *34*, 534–549. [CrossRef]
62. Siddiqui, D.A.; Noor-us-Sahar. The Impact of Training & Development and Communication on Employee Engagement—A Study of Banking Sector. *Bus. Manag. Strateg.* **2019**, *10*, 23–40. [CrossRef]
63. Schaufeli, W.B.; Bakker, A.B.; Salanova, M. The Measurement of Work Engagement with a Short Questionnaire—A Cross-National Study. *Educ. Psychol. Meas.* **2006**, *66*, 701–716. [CrossRef]
64. Sarstedt, M.; Ringle, C.M.; Hair, J.F. Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research*; Springer International Publishing: Cham, Switzerland, 2021; pp. 1–47.
65. Larasati, O.; Dirgahayani, P. Importance-Performance Matrix Analysis (IPMA) Of Transport Disadvantage Variables on Social Exclusion in a Rural Context. *IOP Conf. Ser. Earth Environ. Sci.* **2018**, *158*, 012015. [CrossRef]
66. Albort-Morant, G.; Sanchís-Pedregosa, C.; Paredes Paredes, J.R. Online banking adoption in Spanish cities and towns. Finding differences through TAM application. *Econ. Res. Istraz.* **2022**, *35*, 854–872. [CrossRef]
67. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]
68. Roy, S.K.; Balaji, M.S.; Quazi, A.; Quaddus, M. Predictors of customer acceptance of and resistance to smart technologies in the retail sector. *J. Retail. Consum. Serv.* **2018**, *42*, 147–160. [CrossRef]
69. Jarvis, C.B.; MacKenzie, S.B.; Podsakoff, P.M. A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *J. Consum. Res.* **2003**, *30*, 199–218. [CrossRef]
70. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
71. Soelton, M.; Noermijati, N.; Rohman, F.; Mugiono, M.; Aulia, I.N.; Siregar, R.E. Reawakening perceived person organization fit and perceived person job fit: Removing obstacles organizational commitment. *Manag. Sci. Lett.* **2020**, *10*, 2993–3002. [CrossRef]
72. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
73. Henseler, J.; Hubona, G.; Ray, P.A. Using PLS path modeling in new technology research: Updated guidelines. *Ind. Manag. Data Syst.* **2016**, *116*, 2–20. [CrossRef]

74. Ning, Y.; Yan, M.; Xu, S.X.; Li, Y.; Li, L. Shared parking acceptance under perceived network externality and risks: Theory and evidence. *Transp. Res. Part A Policy Pract.* **2021**, *150*, 1–15. [CrossRef]
75. Hair, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M.; Danks, N.P.; Ray, S. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*; Springer Nature: Cham, Switzerland, 2021.
76. Shmueli, G.; Ray, S.; Velasquez Estrada, J.M.; Chatla, S.B. The elephant in the room: Predictive performance of PLS models. *J. Bus. Res.* **2016**, *69*, 4552–4564. [CrossRef]
77. Shmueli, G.; Sarstedt, M.; Hair, J.F.; Cheah, J.H.; Ting, H.; Vaithilingam, S.; Ringle, C.M. Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *Eur. J. Mark.* **2019**, *53*, 2322–2347. [CrossRef]
78. Cheah, J.-H.; Thurasamy, R.; Memon, M.A.; Chuah, F.; Ting, H. Multigroup Analysis using SmartPLS: Step-by-Step Guidelines for Business Research. *Asian J. Bus. Res.* **2020**, *10*, I–XIX. [CrossRef]
79. Sarstedt, M.; Henseler, J.; Ringle, C.M. Multigroup Analysis in Partial Least Squares (PLS) Path Modeling: Alternative Methods and Empirical Results. In *Measurement and Research Methods in International Marketing*; Emerald Group Publishing Limited: Bingley, UK, 2011; pp. 195–218.
80. Jamal, T.; Zahid, M.; Martins, J.M.; Mata, M.N.; Rahman, H.U.; Mata, P.N. Perceived Green Human Resource Management Practices and Corporate Sustainability: Multigroup Analysis and Major Industries Perspectives. *Sustainability* **2021**, *13*, 3045. [CrossRef]
81. Tensay, A.T.; Singh, M. The nexus between HRM, employee engagement and organizational performance of federal public service organizations in Ethiopia. *Heliyon* **2020**, *6*, e04094. [CrossRef]
82. Jose, G.; Mampilly, S.R. Psychological Empowerment as a Predictor of Employee Engagement: An Empirical Attestation. *Glob. Bus. Rev.* **2014**, *15*, 93–104. [CrossRef]
83. Attaran, M.; Attaran, S.; Kirkland, D. Technology and Organizational Change: Harnessing the Power of Digital Workplace. In *Handbook of Research on Social and Organizational Dynamics in the Digital Era*; Idemudia, E., Ed.; IGI Global: Hershey, PA, USA, 2020; pp. 383–408.
84. Grosseck, G.; Malita, L.; Bunoiu, M. Higher Education Institutions Towards Digital Transformation—The WUT Case. In *European Higher Education Area: Challenges for a New Decade*; Curaj, A., Deca, L., Pricopie, R., Eds.; Springer: Cham, Switzerland, 2020; pp. 565–581.
85. Lanzara, G.F. *Shifting Practices: Reflections on Technology, Practice, and Innovation*; MIT Press: Cambridge, MA, USA, 2016.
86. Ilyasa; Madhakomala; Ramly, M. The Effect of Organization Culture, Knowledge Sharing and Employee Engagement on Employee Work Innovation. *Int. J. Sci. Res. Manag.* **2018**, *6*, 57–63. [CrossRef]
87. Hughes, C.; Robert, L.; Frady, K.; Arroyos, A. Managing People and Technology in the Workplace. In *Managing Technology and Middle- and Low-Skilled Employees*; Emerald Publishing Limited: Bingley, UK, 2019; pp. 91–101.
88. Benavides, L.M.C.; Arias, J.A.T.; Serna, M.D.A.; Bedoya, J.W.B.; Burgos, D. Digital transformation in higher education institutions: A systematic literature review. *Sensors* **2020**, *20*, 3291. [CrossRef] [PubMed]
89. Kley, S. The Impact of Job-Related Mobility and Migration Intentions on Union Dissolution. In *Spatial Mobility, Migration, and Living Arrangements*; Aybek, C., Huinink, J., Muttarak, R., Eds.; Springer: Cham, Switzerland, 2015; pp. 139–158.
90. Kynčlová, P.; Upadhyaya, S.; Nice, T. Composite index as a measure on achieving Sustainable Development Goal 9 (SDG-9) industry-related targets: The SDG-9 index. *Appl. Energy* **2020**, *265*, 114755. [CrossRef]
91. Shamim, S.; Cang, S.; Yu, H. Impact of knowledge oriented leadership on knowledge management behaviour through employee work attitudes. *Int. J. Hum. Resour. Manag.* **2019**, *30*, 2387–2417. [CrossRef]