Global J. Environ. Sci. Manage. 9(3): 403-426, Summer 2023, Serial #35

Global Journal of Environmental Science and Management
(GJESM)

Homepage: https://www.gjesm.net/

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ORIGINAL RESEARCH PAPER

Social learning activities to improve community engagement in waste management program

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ARTICLE INFO

Article History:
Received 30 October 2022
Revised 04 December 2022
Accepted 14 January 2023

Keywords:
Community engagement
Community-based program
Community learning program
Municipal solid waste management (MSWM)
Social learning
Waste management behavior

DOI: 10.22035/gjesm.2023.03.04

ABSTRACT

BACKGROUND AND OBJECTIVES: Community engagement is crucial to overcome environmental issues, including waste management. Several education-based initiatives have been employed to improve community engagement in waste management programs, but the effects were not satisfied in changing resident behavior for sustainable engagement. Some studies suggested social learning as the solution to improve community engagement through practice-based and dialogue-based learning activities. Nevertheless, it needed more empirical evidence to show the effect. This study aimed to measure the effect of social learning on improving individual waste management behavior and how social learning influence it.

METHODS: Using SmartPLS 3.2.9, this study measured the causal relationship of social learning activities to individual affective and behavioral factors. This study involved 504 residents exposed to social learning activities in Kawasan Bebas Sampah/ Zero Waste Area program in Bandung City, Indonesia as the respondents to gather the data using survey method.

FINDINGS: The study found that social learning activities have significantly influenced waste management behavior indirectly through Affective factors. The data showed that Dialogue-based learning has no significant effect on Affective factors for all significance levels (β =-0.0862, P > 0.01). Instead, path model analysis indicated the mediating effect of Practice-based learning for Dialogue-based learning and Affective Factors, with the accuracy model at a moderate level (R2 = 42%; Q2 = 0.2258). Meanwhile, supporting facilities influenced both Practice-based learning (β = 0.3116, P < 0.001) and Affective factors (β = 0.4419, P < 0.001) significantly. Further path model analysis demonstrated that without "Affective Factors" being nurtured, learning activities and Facilities would not be able to improve behavior significantly, as all paths directing to Behavioral Domain (Intention and WMB) had an insignificant effect (P value > 0.05).

CONCLUSION: This study offered empirical evidence, showing the mechanism of social learning to improve waste management behavior. The Learning activities should combine Dialogue and Practice-based learning to influence waste management behavior significantly, while Affective factors become the direct effect of Learning Activities. Supporting facilities were required to support the learning by providing routine waste collection systems and recycling facilities beneficial for the residents. In order to improve the learning activity effectiveness, the facilitators need to pay more attention to the learning contents to nurture the expected Affective factors.

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
87	7	8

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Note: Discussion period for this manuscript open until October 1, 2023 on GJESM website at the "Show Article".

INTRODUCTION

Household or residential waste has dominated municipal waste composition in many developing countries (Banerjee and Sarkhel, 2020; Esmaeilizadeh *et al.,* 2020; Speier *et al.*, 2018; Jouhara *et al.*, 2017), including Indonesia (SIPSN, 2021). This dominance shows that residents are one of the core stakeholders for MSWM improvement (Aleluia and Ferrão, 2016; Kamaruddin *et al.*, 2017; Moh and Abd Manaf, 2017; Owamah *et al.*, 2017). Some literature also indicated that the residents play crucial roles in waste prevention, reduction, reuse, and recycling which become critical activities in MSWM (Al-dailami *et al.*, 2022; Soni *et al.*, 2022; Zorpas, 2020). Thus, residents are expected to engage the waste management sustainability actively. In environmental issues, community engagement allows heterogeneous people to act collectively for a more impactful program (Axon, 2016). Community engagement refers to not only reducing the risk of unsupported community to the waste management program (Goven *et al.*, 2012; Kallis *et al.*, 2021; McAfee *et al.*, 2021) but also changing community awareness, attitude, and behavior or lifestyle to support the waste management activities sustainably (Soni *et al.*, 2022; Axon, 2016, 2020). However, establishing proper engagement in waste management activities and sustaining their behavior is still difficult to reach (Axon, 2016; Azevedo *et al.*, 2021; Banerjee and Sarkhel, 2020; Gundupalli *et al.,* 2017). The terminology of engagement refers to not only knowing about the issue (cognitive) but also caring and being motivated internally (affective) and being able to take actions related to the issues (behavior) (Axon, 2016). It implies that the residents are internally motivated to join the waste management activity because their psychological factors agree, and they know how to do it and can do it. Osborne *et al.* (2021) also stated that community engagement means direct participation and involvement in social learning activities to improve understanding and interest in the addressed issues. This engagement will build trust as social capital among participants, change the community behavior, and willingness to collectively act for sustainable practice (Axon, 2016; Goven *et al.*, 2012; Osborne *et al.*, 2021). Several attempts were employed to improve community engagement in waste management activities through various interventions such as awareness campaigns or other educational-based strategies. However, some interventions only occurred temporarily (Gyimah *et al.*, 2019; Singer *et al.*, 2019; Yukalang *et al.*, 2018; Zamri *et al.*, 2020), causing temporary changing behavior only during the intervention (Bui *et al.*, 2020; Noguera-Méndez *et al.*, 2016; Zamri *et al.*, 2020). Some interventions were ineffective in changing the behavior due to their ineffectiveness in the process (Esmaeilizadeh *et al.*, 2020; Idamah, 2015; Moh and Abd Manaf, 2017; Setiawan *et al.*, 2019; Wang *et al.*, 2018). Meanwhile, other interventions relied only on a mass-based education approach, only facilitating one-way communication without any interaction, such as television (Almasi *et al.*, 2019; Idamah, 2015; Song *et al.*, 2016), articles/newspapers (Chow *et al.*, 2017; Song *et al.*, 2016), social media/internet (Hammami *et al.*, 2017; Ma *et al.*, 2018). Such an approach only works for those who already have awareness and attitude toward waste management activities. According to previous studies, two-way communication and close interaction have become one of the core processes to build community engagement by changing their behavior sustainably (Axon, 2016; Osborne *et al.*, 2021; Vetter, 2020). Active action is also crucial for empowerment and ownership of the program (Osborne *et al.*, 2021). Enabling active action allows the community to perceive the values of the activities and improve their awareness and attitude toward the activities so that it builds new behavior, and develop new culture (Knickmeyer, 2020; Liao, 2018; Xu *et al.*, 2017; Yeh *et al.*, 2016).

Social learning for community engagement sustainability in waste management

To achieve sustainable community engagement in the waste management process, some literature suggested long-term intervention in the form of social learning to encourage sustainable improved behavior (Almasi *et al.*, 2019; Bui *et al.*, 2020; Idamah, 2015; Knickmeyer, 2020; Loan *et al.*, 2017; Navykarn and Muneenam, 2015; Noguera-Méndez *et al.*, 2016; So *et al.*, 2019; Sukholthaman and Shirahada, 2015; Zamri *et al.*, 2020). Social learning has been recommended as one approach to enable collective learning in various environmental-based programs for both developing and developed countries (Barrantes and Yagüe, 2015; Benítez *et al.*, 2020; Benson *et al.*, 2015; Goven *et al.*, 2012; Kristjanson *et* *al.*, 2014; Noguera-Méndez *et al.*, 2016). One of the approaches to implementing social learning in the community is using a framework called Community of Practice (CoP) (Kristjanson *et al.*, 2014; Madsen and Noe, 2012; Noguera-Méndez *et al.*, 2016; Tran *et al.*, 2018). The CoP concept was introduced by Wenger *et al.* (2002), who designed CoP as a source of learning for a particular community. The key to community engagement sustainability is the critical reflection on the relationship between knowledge (cognitive), affective, and action correlated with environmental problems (Abramowitz *et al.*, 2017; Axon, 2016; Keen and Mahanty, 2006; Noguera-Méndez *et al.*, 2016). Social learning can facilitate it by enabling individuals, communities, and societies to learn through dialogue and practice and adapt their behavior to deal with change to achieve sustainability (Kristjanson *et al.*, 2014; Noguera-Méndez *et al.*, 2016; Tran *et al.*, 2018). In the social learning framework, learning and collective change become the core of engagement, addressing complex socio-ecological problems by joining various knowledge and value sharing at distinct levels (Keen and Mahanty, 2006; Noguera-Méndez *et al.*, 2016). Through a dialogue and practice, social learning contributes to achieving more sustainable change in resident behavior toward waste management activities as it facilitates single-loop, double-loop, and even triple-loop learning (Keen and Mahanty, 2006; Noguera-Méndez *et al.*, 2016). While single-loop learning is impactful in changing technical actions such as skills and procedures, double-loop learning modifies internal factors such as individual value, assumptions, belief, motivation, awareness, and intention through a mental model that defines the actions or behaviors (Keen and Mahanty, 2006; Noguera-Méndez *et al.*, 2016). Triple loop learning goes beyond the individual, as it is the deepest level of learning as it modifies systems and nurtures social capital, such as changing social norms, law, and social culture (Keen and Mahanty, 2006; Noguera-Méndez *et al.*, 2016) for sustainable community engagement (Goven *et al.*, 2012; Osborne *et al.*, 2021). Social learning promotes effective learning as it is characterized as an iterative process of knowledge sharing through joint activities such as dialogue, collective action, and reflection. The activities encourage changes in practice, not only at an individual level but also in networks and systems, to reach a particular shared purpose (Keen and Mahanty, 2006; Kristjanson *et al.*, 2014; Noguera-Méndez *et al.*, 2016). Thus, social learning approach changes individual and community behavior toward waste management to reach sustainable waste management practice.

Research gaps and aim of the study

Social learning in the form of CoP has been implemented in a variety of domains in order to change community behavior, for instance, an agricultural-based community in Denmark (Madsen and Noe, 2012), South Australia (Raymond and Robinson, 2013) and Sweden (Nykvist, 2014). It was also implemented in learning groups of farming residents in Indonesia (Wulandhari *et al.*, 2021), Vietnam (Tran *et al.*, 2018) and dairy farmers in Europe (Dolinska and d'Aquino, 2016; Triste *et al.*, 2018). Some collective learning and action groups for the environmental initiatives are Canadian biosphere partnership communities across Canada (Reed *et al.*, 2014), Green Action Co-op in England (Bradbury and Middlemiss, 2015), and waste management learning activities in community-level Kawasan Bebas Sampah (KBS)/ Zero Waste Area (ZWA) in Bandung City, Indonesia (Ghazali *et al.*, 2021; Sunarti *et al.*, 2020). Even though social learning has been implemented in various domains and has shown its effects to change community behavior, it lacks of empirical evidence to show how it could affect community behaviors. Most previous studies focused on identifying the learning activities (both dialogue-based and practice-based learning) (Dolinska and D'Aquino, 2016; Jordan *et al.*, 2020; Noguera-Méndez *et al.*, 2016; Reed *et al.*, 2014; Tran *et al.*, 2018; Wulandhari *et al.*, 2021). Some other studies discussed only the learning outputs (Bradbury and Middlemiss, 2015; Dolinska and D'Aquino, 2016; Noguera-Méndez *et al.*, 2016; Nykvist, 2014; Vetter, 2020; Wulandhari *et al.*, 2021). Nevertheless, it was a lack of empirical evidence to measure how significant each social learning activity can affect the individual affective factors and behavior. Therefore, this study aims to measure the effect of social learning, characterized by dialogue and practice learning approach, on the individual behavior especially concerning waste management behavior domain. In order to facilitate the mapping of social learning activities, it was employed Socialization, Externalization, Combination, and Internalization (SECI Model) by Nonaka *et al.* (2008), which are four postulates introduced by Nonaka *et al.* (2000) to explain the knowledge conversion among four different modes. According to Nonaka *et al.* (2008), there were primarily two types of learning to facilitate SECI: Practice-based learning and dialogue-based learning. Dialogue-based learning was powerful in facilitating externalization and combination as tacit knowledge can be expressed into formal language, and explicit knowledge can be deepened and refined (Nonaka *et al.*, 2008). Meanwhile, practice-based learning facilitates Socialization and Internalization as this activity allows sharing of tacit knowledge via shared experience and explicit knowledge embodiment into action as tacit knowledge (Nonaka *et al.*, 2008). This study was the follow-up of the current study by Ghazali *et al.* (2021), which proposed a model showing the relationship between two approaches of social learning (Dialogue and Practice) to Affective and behavioral factors through the qualitative method. This study was intended to give empirical evidence of the relationship among factors in the model and showed how social learning influenced waste management behavior. The study was located in *KBS* or Zero Waste Area, in Bandung City – West Java, Indonesia, based on Ghazali *et al.* (2021) study location. Bandung City is one of the cities in Indonesia that encourage community engagement in the municipal waste management system (Sunarti *et al.*, 2020), besides several other cities in East Java (Trihadiningrum *et al.*, 2017). This study was conducted in April-July 2021, located in eight sub-districts (*Kelurahan*) chosen as ZWA models in Bandung City, West Java, Indonesia.

MATERIALS AND METHODS

This study used a quantitative method, using a survey strategy to gather the data from eight locations of the ZWA Program located in Bandung City, West Java, Indonesia, as presented in Fig. 1.

This study focused on exploring the effect of social learning activities on residents' behavior toward waste management activities in the 8 locations of the ZWA program. Bandung City government was concerned with handling the waste problem by involving residents actively in the waste management system because the waste composition in Bandung City was dominated by food waste (as presented in Fig. 2) which was most likely from residential or households (Ghazali *et al.*, 2021). The resident involvement in the waste management system at the ZWA program was mainly in inorganic-organic waste separation (highly encouraged/mandatory) and organic waste recycling (encouraged). Waste collectors collected, and recycled the organic waste at recycling points around the ZWA areas. The residents can sell the inorganic waste at a Waste Bank or just give them freely to the waste collectors for their additional income. There were also simple recycling facilities provided, such as bio pores or many types of composters or biodigesters, at some locations in ZWA areas (Ghazali *et al.*, 2021) so residents could directly dispose of and recycle their waste if they were willing. In some areas without enough spaces for recycling points, the organic waste was transferred to city-level recycling points.

The total population of all studied areas reached 34.877 households, with a different number of each ZWA. The respondents were the person in the family who handled the household waste disposal in the study location. Therefore, the sample number was taken from each ZWA proportionally. Each sub-district had several hamlets (Rukun Warga/RW). Not all hamlets in every sub-district were actively involved in the program; therefore, the sample selection was taken only from the areas exposed to learning activities under ZWA program. The total number of residents in the areas exposed to the learning activities became the population. The total number of required samples was counted using Cochran's sample as Eq. 1 (Cochran, 1977).

$$x = \frac{Z^2 pq}{e^2} \tag{1}$$

The x in the above formula refers to the sample size. Assuming that the confidence level (Z) was 95% (resulting Z score of 1.96), the standard deviation (p) was 0.5, so that q became 1-0.5 = 0.5 (1-p), and the margin of error (e) 0.5, the number of samples required was 395. However, was provided 504 samples to make sure getting adequate data and anticipating data errors from the respondents during the data collection process. Detailed information about the sample is presented in Table 1.

The study sample was chosen through a combination of purposive and clustered random sampling, as presented in Fig. 3. Purposive sampling was conducted for specific situations in which the

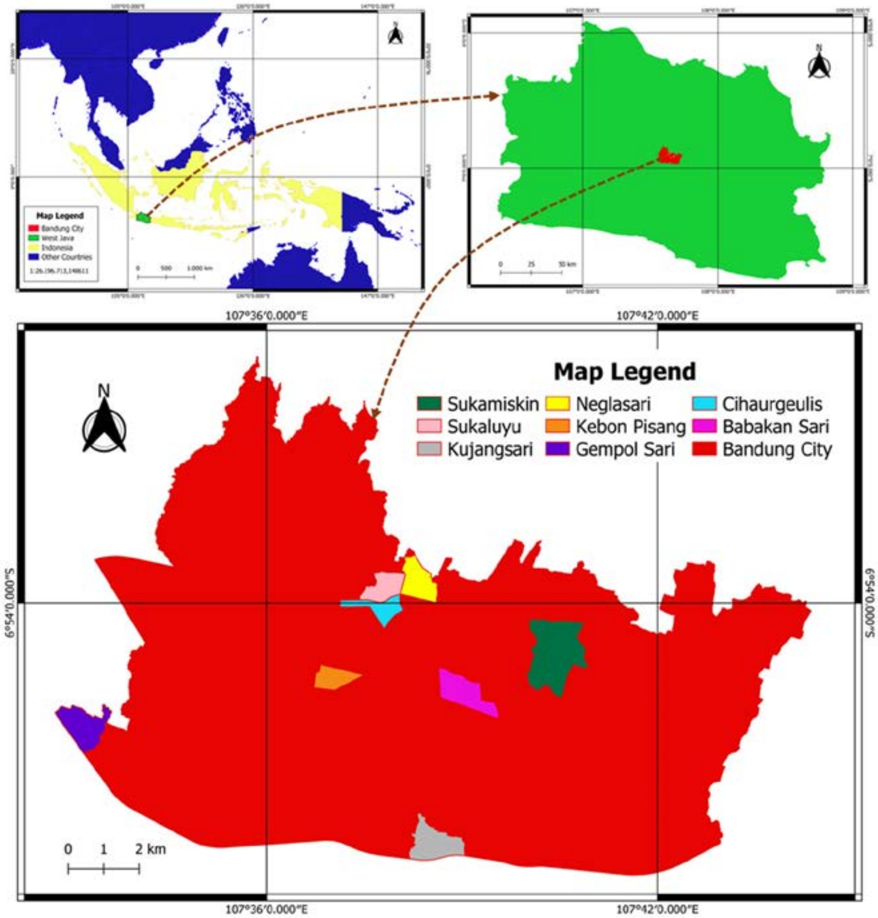

Fig. 1: Geographic location of the study arae plotted using an open source QGIS free software
(a) The study area Geographical location in Indonesia and its surrounding continents.
(b) West Java map were Bandung City is located (c) The study area with the eight study location points

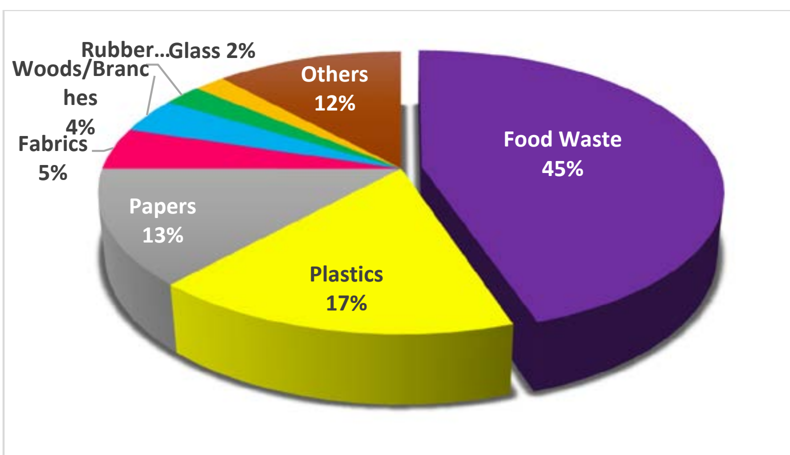

Fig. 2: Waste Composition in Bandung City, West Java, Indonesia (SIPSN, 2022)

Table 1: The Number of population in ZWA areas and samples for survey

No	ZWA areas	Number of households involved actively in waste management program	Sample prediction	Sample
1	Babakansari	± 500	50-70	70
2	Cihaur Geulis	± 800	80 - 100	103
3	Gempolsari	± 300	30 - 50	30
4	Kebon Pisang	± 400	40 - 60	60
5	Kujangsari	± 300	30 - 50	30
6	Neglasari	± 400	40 - 60	71
7	Sukaluyu	± 200	20 - 40	40
8	Sukamiskin	± 800	80 - 100	100
	Total number	± 37.000	370 - 530	504

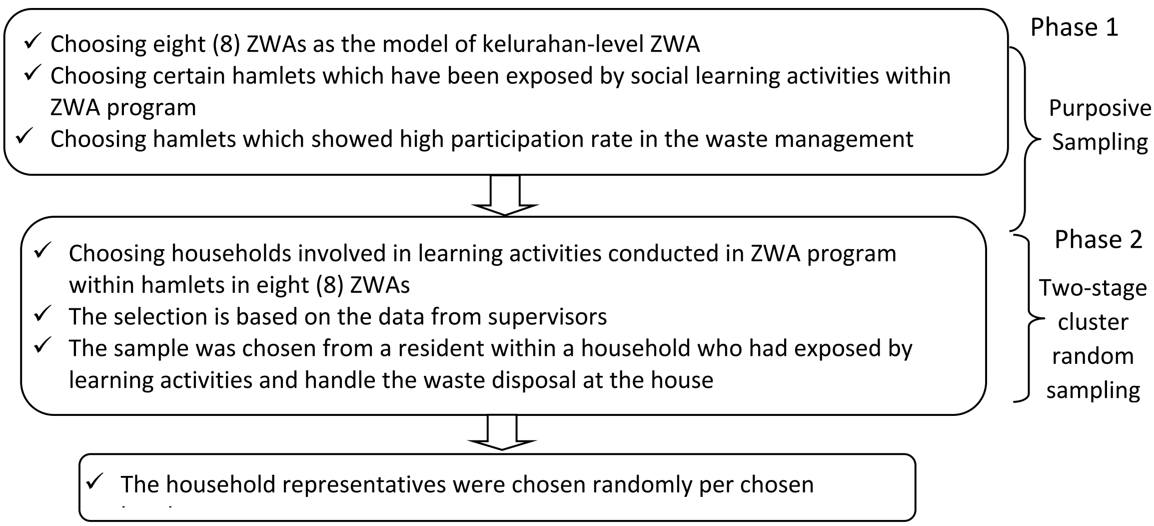

Fig. 3: Sampling technique for the respondents

sample selection was based on specific characteristics or requirements to enable the researchers to get broader information related to the purpose of the study (Neuman, 2014). The sample was first selected by choosing hamlet involved actively in learning activities, identified from the data of the supervisors. The households chosen as the respondents were randomly chosen to allow diverse resident profiles from each area.

Hypotheses building

According to qualitative data findings related to social learning activities in the ZWA program in Bandung City, Indonesia, two primary learning activities involved residents directly: Practice-based learning and Dialogue-based learning. The unit of analysis focused on residents, so some variables, such as key stakeholders' support and critical stakeholders' learning process, were excluded from the discussion. Both learning activities represented Socialization, Externalization, Combination, and Internalization. According to the informants, dialogue-based learning became the initial step of practice-based learning in which residents who had been given socialization through various approaches, such as Door-to-Door Education (DTDE), were asked to practice waste separation directly the next day. Therefore, some facilities were required, such as a waste collection system handled by the officers, separate waste bins, and recycling tools in the local areas. Therefore, the residents could separate their waste directly, recycle their waste if

Table 2. Hypotheses of the quantitative phase

	Hypothesis
H1	Dialogue-based learning activities significantly influence Practice-based learning activities
H2	Dialogue-based learning activities significantly influence affective factors
H3	Practice-based learning activities significantly influence affective factors
H4	Supporting Facilities system significantly influence Practice-based learning activities
H5	Supporting facilities system for significantly influence affective factors
H6	Affective factors significantly influence Intention to do waste management
H7	Intention to do waste management significantly influence WMB
H8	Dialogue-based learning activities significantly influence WMB
H9	Practice-based learning activities significantly influence WMB

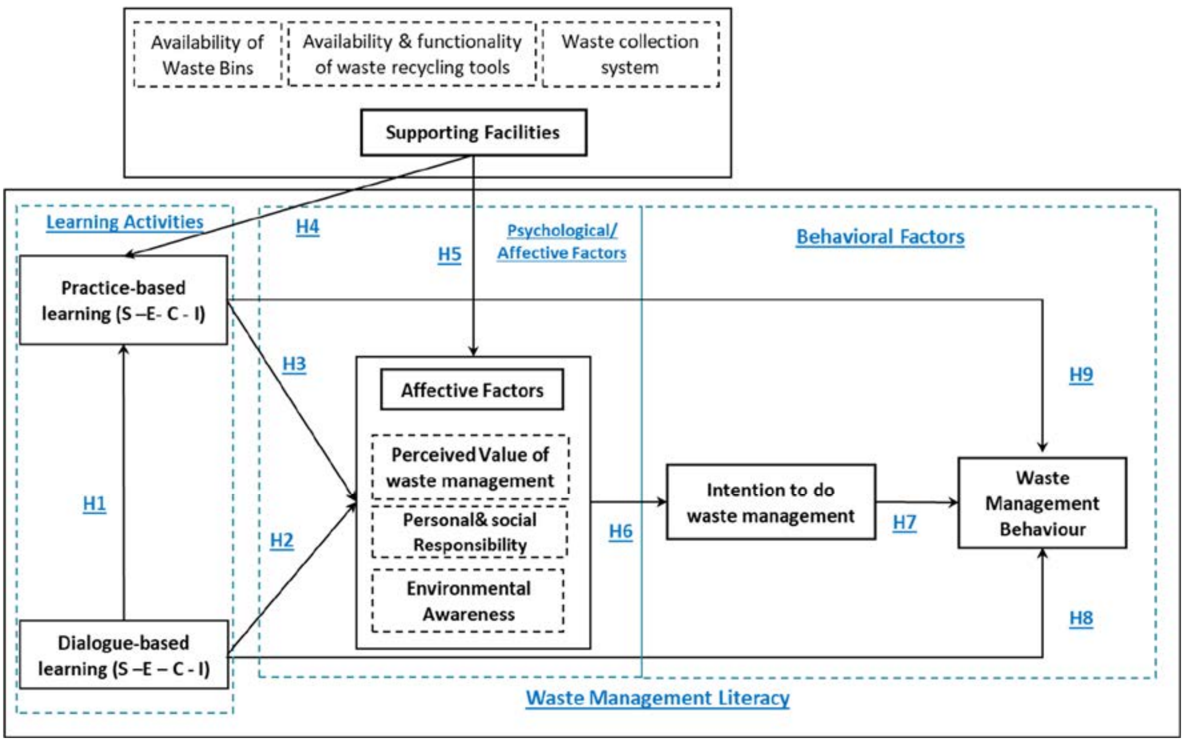

Fig. 4: Proposed model of the study

possible and feel the value of the activity. Learning activities in the ZWA program influenced Affective Factors resulting from individual self-reflection on double-loop learning. The Affective Factors identified and predicted to be impactful to waste management behavior (WMB) were Environmental awareness, Personal and Social responsibility, and Perceived value of waste management, precisely economic value, environmental value, social value, and religious value. The affective factors were predicted to nurture the behavioral factors represented through intention to participate and WMB. This study hypothesized that affective factors should mediate the relationship between learning activities and behavior. Therefore, to strengthen the hypotheses, the effect of learning activities on behavior was also measured for comparison. Therefore, several hypotheses describing the relationship among variables can be developed, as presented in Table 2. The proposed model that showed the overall relationship of all hypotheses measured in this study is presented in Fig. 4.

Questionnaire development

This study aims to measure the effect of social learning activities among households in the ZWA program by implementing the Partial Least Square Structural Equation Model (PLS-SEM) using SmartPLS 3.2.9. The measurement items in the questionnaire used in this study were established mainly from the findings in the qualitative phase on the study location (Ghazali *et al.*, 2021), combined with the literature review (Sunarti *et al.*, 2021). The literature review provided several significant variables affecting waste management behavior and predicted items to measure the variables. The qualitative findings determined which variables would be measured through the quantitative phase. The final questionnaire was refined based on the finding from the qualitative phase. Each indicator was measured by at least two indicators or measurement items. Each measurement item represented the construct weighting (Hair *et al.*, 2017). All indicators were ordinal, illustrated by the Likert scale with different points in some variables (3 points Likert point, 4 points Likert scale and 5-point Likert scale). The questionnaire was validated through two steps: expert validation and pilot test. The measurement items in the questionnaire before expert validation were 47 items. Three experts validated the questionnaire, resulting in three items being deleted because having similar meanings to other measurement items. Fifteen items were fixed without any revision, while twenty-nine items were revised in the sentences to make them more understandable and relevant to the measured variables. The pilot test involved 30 respondents, but the revision was only on the sentence structures especially in the clarity and ambiguity, without any item deletion. Once the data collection had been conducted, statistical reliability and validity tests were employed. Hair *et al.* (2017) recommended three common indicators to evaluate the reliability and validity of the model proposed: composite reliability, individual factor loading, and average variance extracted (AVE) to confirm the accuracy of latent variables measurement, the discriminant and convergent validities. The composite reliability (CR) value was associated with internal consistency among the involved latent variables, in which the threshold was 0.6 (Hair *et al.*, 2017), indicating that the internal model's consistency was robust. The threshold value for the individual loading factor was 0.5 to be significant. The AVE score was to show the discriminant and the convergent validities in which the higher the score, the greater the validities of the latent variables. The recommended value based on Fornell and Larcker was 0.5 and above (Hair *et al.*, 2017). The evaluation of the structural model (inner model), based on Hair *et al.* (2017), consisted of several steps because the primary goal of PLS-SEM was not only identifying significant path coefficients but also the relevance and significance of the effects. The overall evaluation process of structural model evaluation is presented in Fig. 5.

RESULTS AND DISCUSSION

Demographic characteristics of respondents

Detailed information about the demographic data of the respondents in this study is presented in Table 3. According to Table 4, respondents were 100% female because the chosen respondents were those who handled the waste disposal at home. The respondents were dominated by housewives (62,7%) while the age was spread, with the highest percentage: 40-49 years old (30,8%). The majority of the education level of the respondents was low because 81,2 % of the respondent's latest education was elementary-high schools. Meanwhile, the economic level was dominantly lower-middle class.

The profile of learning sources

Before residents filled out the questionnaire, the profile of learning sources was surveyed to ensure that the residents were involved in the learning activities in the ZWA program. The survey result was presented in Fig. 6.

According to the survey of learning sources from the respondents, it was found that the dominant learning sources were critical stakeholders in the ZWA program: DLHK educators (15.1%), KANG PISMAN cadres (14.6%), local cadres (PKK, Karang Taruna) (12.5%), local leaders (RT, RW) (12.3%), neighbourhoods 10.3%. This finding could prove that the ZWA learning program impacted the residents. It also indicated the crucial roles of educators from various resources, including the involvement of local people (including KANG PISMAN cadres, local leaders, waste collectors and neighbourhoods) to persuade the residents intensively. Employing local people in the community allows intensive interaction as they meet each other daily. This finding confirmed the

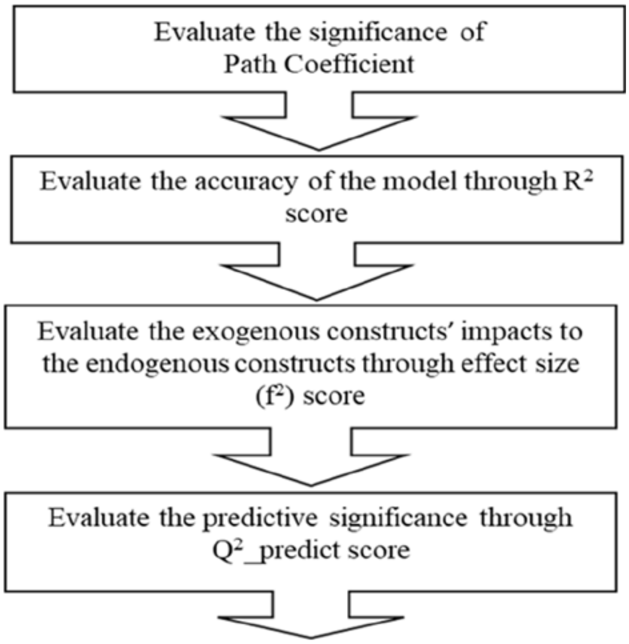

Fig. 5: The Procedure of structural model evaluation

Table 3: Demographic data of respondents

Variables	Frequency	%
Age		
20-29 Years Old	53	10.5
30-39 Years Old	111	22
40-49 Years Old	155	30.8
50-59 Years Old	132	26.2
> 60 Years Old	53	10.5
Occupation		
Housewives	316	62.7
Employees	188	37.3
Education Level		
Elementary-High Schools	409	81.2
Diploma	36	7.1
Bachelor	55	10.9
Postgraduate	4	0.8
Household Expense (/Month)		
Rp. 800,000,00-Rp. 1,810,000,00	293	58.1
Rp. 1,810,000,00-Rp. 4,572,000,00	185	36.7
More than Rp. 4,572,000,00	26	5.2

study by Pei (2019), who found that neighbourhood ties were crucial to support community learning about waste management in China. It could also be evidence that group learning (in a community) was essential to allow more interaction among neighbours. Knowles (1984) also pointed out social relationship to encourage adult learning. This data also showed that utilizing the internet and social media nowadays plays

Table 4. The reliability and convergent validity of improved model with deleted items

Constructs	Items	Outer loadings	Cronbach's α	CR	AVE
Dialog	DL1	0.5576			
	DL3	0.8140			
	DL4	0.7314	0.7281	0.8189	0.4814
	DL5	0.7753			
	DL6	0.5455			
Practice	PL1	0.6509			
	PL3	0.7253	0.6378	0.7847	0.4817
	PL4	0.5956			
	PL6	0.7441			
Supporting Facilities	WB1	0.3820			
	WB2	0.3276			
	WC1	0.7038			
	WC2	0.7390	0.6027	0.7395	0.3115
	WR1	0.3058			
	WR2	0.5133			
	WR4	0.7236			
Affective Factors	UR1	0.2812			
	UR2	0.6710			
	UR3	0.7653			
	UR4	0.3642			
	PV2	0.5546			
	PV3	0.6947	0.8446	0.8729	0.3777
	PV4	0.7034			
	PV5	0.4856			
	EA1	0.7006			
	EA2	0.5817			
	EA3	0.6039			
	EA4	0.7553			
Intention	I1	0.7341			
	I2	0.6985			
	I3	0.6410	0.7451	0.8306	0.4959
	I4	0.6899			
	I5	0.7524			
WMB	B1	0.6582			
	B2	0.6211			
	B3	0.6688	0.7185	0.8163	0.4718
	B4	0.7615			
	B5	0.7159			

a vital role in disseminating and socializing knowledge to a diverse society. However, these sources of learning only became additional to strengthen the effect of intensive learning, as indicated by Jiang *et al.* (2021). Furthermore, Sujata *et al.* (2019) pointed out that social media and websites could be utilized for knowledge storage while also becoming a learning source to reach residents outside the boundary area.

Data cleaning process

Before the data was analyzed using SmartPLS 3.2.9, data issue identification was conducted to delete some invalid and unreliable data. It could be done by measuring the Skewness and Kurtosis in SmartPL 3.2.9 or using BoxPLot in SPSS. In this study, it was employed the BoxPlot test using SPSS. The data from respondents were considered invalid when they showed extreme or unusual responses compared to the others or the question items. As a result, there were 33 data issues identified. After a manual screening, eight data issues were acceptable due to showing unique outliers to gave different insights for the findings, as Hair *et al.* (2017) implied that some outliers showing interesting cases may still be

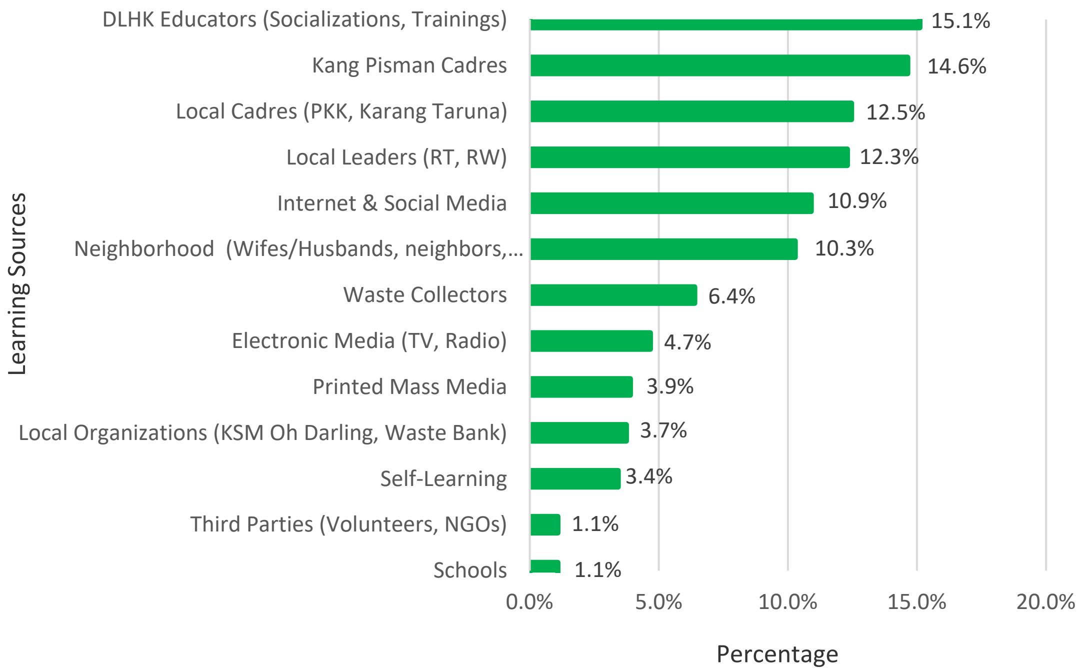

Fig. 6: Learning sources of residents in ZWA Program

Table 5: The discriminant validity of the revised model

Laten variable	Fornell-Larcker Criterion					
	Affective	Dialog	Facilities	Intention	Practice	WMB
Affective	0,6146					
Dialog	0,2196	0,6938				
Facilities	0,5922	0,2363	0,5582			
Intention	0,2795	0,2642	0,3225	0,7042		
Practice	0,5298	0,4901	0,5025	0,3124	0,6940	
WMB	0,3581	0,3679	0,3406	0,5802	0,3801	0,6868
Latent variable	Heterotrait-monotrait ratio (HTMT)					
	Affective	Dialog	Facilities	Intention	Practice	WMB
Affective						
Dialog	0,2735					
Facilities	0,7139	0,3657				
Intention	0,3415	0,3693	0,4707			
Practice	0,6655	0,6847	0,8071	0,4563		
WMB	0,4321	0,5192	0,5065	0,7830	0,5644	

required. Therefore, the eight data issues were still included in the analysis. The data issues excluded were those giving “Inconsistent Answer”, “Straight lining”, and “Outlier”. Therefore, from the 504 total responses, with 25 exclusions, the final respondents became 477. Hence, the further analysis only involved 477 responses.

Outer model analysis

The outer model analysis consists of analysis toward reliability and validity of the measurement items such as Internal Consistency Reliability (Cronbach’s Alpha), Composite Reliability (CR), Convergent Validity (AVE) and Discriminant Validity (Fornel Lacker Criteria and HTMT). As the questionnaire used in this study was based on qualitative findings, an exploratory analysis was conducted to eliminate invalid and unreliable measurement items to improve the validity and reliability of the overall measurement items. The first reliability and validity test output are presented in Tables 4 and 5.

Hair *et al.* (2017) suggested that increasing the validity and reliability of the measurement ítems could be done by deleting some less reliable and valid ítems (rules of thumbs for explorative study: 0.5) as long as the deletion could increase the overall reliability and validity score. According to Tables 5 and 6, some deletions of several items with outer loadings < 0.5 had increased the score for both Cronbach’s α and CR. Similarly, deleting the higher-order constructs made the Discriminant Validity on Fornell-Larcker Criterion, and HTMT met the requirement. The subsequent problems were found on AVE. Due to the deleted items, the AVE score had improved, but the score was not reaching the standard yet. Thus, some more deletions of items were conducted. Some items with lower outer loading score were deleted to improve the AVE score. Thus, the final measurement ítems based on outer model evaluation were presented in Tables 6 and 7.

According to Table 6, some deletions of items with low outer loadings improved AVE and Cronbach’s Alpha score. A similar situation was found for Discriminant Validity, in which the diagonal square of AVE was the highest.

Therefore, the final model evaluated in the next step only involved the items that passed the reliability and validity criteria. It is concluded that the valid and reliable items to describe Dialogue-based learning activities were from Externalization and Combination activities, for instance, involvement in informal discussion activity (Externalization) or training events conducted in the community. Meanwhile, items that described practice-based learning activities were Socialization and Internalization, in the form of learning directly to officers/cadres/neighbourhood about waste separation technique (Socialization) and learning by doing the waste separation every day. The direct practice enabled them to experience the effect of the routine activity (Internalization). These findings confirmed what Nonaka *et al.* (2008) explained: Socialization and Internalization occurred through direct experience, while Externalization and Combination occurred through dialogue and reflection. The reliable and valid predictors of supporting facilities were presented by waste collection system and recycling facility support, while waste bin distance and availability were could not predict it. Affective factors were significantly predicted by personal and social responsibility, environmental and social perceived value, and environmental awareness. The predictor of environmental awareness was significantly reflected by two occasions familiar to the respondents in ZWA areas, flood disasters and environmental pollution, as indicated by (Knickmeyer, 2020) and Lawrence *et al.* (2020). Regarding Intention and WMB variables, only organic waste recycling activities were invalid in predicting waste management intention and behavior. It is because, in the ZWA program, organic waste recycling activities became the responsibility of waste officers, while it was only voluntary for residents. However, recycling infrastructure was available in the neighbourhood, such as Bio pores, and composters, to facilitate the residents.

Structural model (Inner model)

The evaluation of the structural model is based on bootstrapping and blindfolding test procedures. The output for the evaluation model for both direct and indirect analysis was presented in Table 8, while the path model is presented in Fig. 7.

The effect of extrinsic factors on residents’ affective factors

Two types of extrinsic factors were involved in the model: learning activities (dialogue-based and practice-based learning) and facilities. Each Extrinsic

Table 6: The final outer model

Constructs/latent variable	Item Code	Measurement items	Outer Loading	Cronbach's α	CR	AVE
Dialog	DL3	Do you often involve in discussion activities related to recycling waste?	0.8721			
	DL4	Do you often involve in training activities about making something from any kind of waste?	0.7982	0.8392	0.8818	0.5547
	DL5	I involve composting training so I can improve my composting skill	0.7606			
Practice	PL1	I learn how to compost/making handicraft from waste with the officer/cadre	0.6401			
	PL3	I understand how to separate waste correctly by practicing everyday	0.7826	0.7397	0.8523	0.6588
	PL6	Separating waste everyday makes me understand the benefits	0.8453			
Supporting facilities	WC1	Separated waste in my house was collected everyday by the officers	0.8128			
	WC2	Separated waste in my area was picked up routinely	0.8338	0.7464	0.8529	0.6592
	WR4	I hope the waste recycling facilities in my area give further benefits for us	0.7884			
Affective factors	UR2	I feel it is my responsibility to separate my waste at home	0.6979			
	UR3	Waste issue in our society can be solved if people and government have responsibility to overcome the problems	0.8009			
	PV3	I feel my house cleaner and more comfortable after I separate waste	0.7462	0.7088	0.8207	0.5344
	PV4	Separating waste will help the waste officer to do their job	0.7248			
	EA1	I am afraid that waste will pollute my environment	0.7191			
	EA4	I am afraid that flood will occur if I do not separate waste	0.7451			
Intention	I1	Are you willing to separate your organic waste (vegetables, fruits, etc)?	0.7636			
	I3	Are you willing to reduce your waste?	0.6640	0.6267	0.8028	0.5789
	I4	Are you willing to separate your inorganic waste (plastics, bottle, etc)?	0.7444			
	I5	Are you willing to take benefits of your inorganic waste?	0.7480			
WMB	B1	Are you used to separating your organic waste?	0.6921			
	B3	Are you used to reducing your waste with any kind of ways (ex: prefer reusable bag, bottle, etc to avoid disposable bags)	0.6607			
	B4	Are you used to separating your inorganic waste?	0.8266	0.6952	0.8141	0.5245
	B5	Are you used to utilizing inorganic waste for more valuable things? (example: making handicraft or other recycled products, etc)	0.7064			

factor path model was discussed in the following sub-chapter:

The effect of learning activities on affective and behavioral factors

Based on the structural model evaluation result presented in Table 8, it was shown that the Dialogue-based learning had no effect on Affective Factors directly, because the total effect is not significant (β = -0.0862, P value 0.070) which does not meet the threshold criteria (P <0,05). The effect level was also 0,0099, considered "no effect" according to Hair *et al.* (2017). However, Dialogue-based learning has médium significance to Practice-learning, with

Table 7: The final discriminant validity of the outer model

Latent variable	Fornell-Larcker criterion					
	Affective	Dialog	Facilities	Intention	Practice	WMB
Affective	0,7448					
Dialog	0,1688	0,8116				
Facilities	0,5708	0,1701	0,8119			
Intention	0,2755	0,1487	0,2717	0,7310		
Practice	0,5009	0,4830	0,3856	0,2688	0,7608	
WMB	0,3444	0,2618	0,2911	0,5736	0,3208	0,7242
Latent variable	Heterotrait-Monotrait ratio (HTMT)					
	Affective	Dialog	Facilities	Intention	Practice	WMB
Affective						
Dialog	0,2063					
Facilities	0,7013	0,2194				
Intention	0,3493	0,2057	0,3674			
Practice	0,6789	0,7086	0,5425	0,4020		
WMB	0,4395	0,3789	0,3934	0,8077	0,4785	

the P value reaching the minimum criteria for all significance levels. Meanwhile, the total indirect effect of Dialogue & Practice path analysis is significant, except the path that did not through Affective Factors (β = 0.0155, P Value 0.4610). It indicated that Dialogue-based learning should be mediated by Practice-based in order to be impactful to "Affective Factors", while the Affective Factors should be the learning activity result, instead of behavioral factors directly. In contrast, all path that showed the direct relationship between Dialogue and Affective Factors presented P Value below all threshold indicating no significant efffect found for the relationship. These path analyses strengthen the evidence that Dialogue should be mediated by "Practice", to significantly affected "Affective Factors". The mediating effect of "Practice-based learning" for "Dialogue-based learning" and "Affective Factors" was considered a moderate level, according to the f^2 effect value (see Table 8 for H1 and H3). Based on Fig. 7, the power of the model to explain "Practice-based learning" was up to 32,6%, weighed as "moderate" (Hair *et al.*, 2017). This finding has confirmed the crucial roles of combining Dialogue and Practice as a unit of learning approach facilitated by the CoP concept (Madsen and Noe, 2012; Nonaka *et al.*, 2008; Tran *et al.*, 2018). This finding also indicated the importance of habituation from practice-based learning as one of the most potent ways to achieve sustainable waste management behavior (Knickmeyer, 2020; Lawrence *et al.*, 2020; Liu *et al.*, 2018). The habituation activity implied that the dialogue and practice-based learning should be employed regularly in the long term because it takes time to change affective factors (Zebua and Sunarti, 2021; Yeh *et al.*, 2016). Considering the outer model finding as presented in Table 6, it pointed out that social learning need to start from a verbal communication approach (formally or informally), for instance dialogue or interaction in training activities, to allow the educators sharing fundamental knowledge and values with the residents (Sunarti *et al.*, 2021). Moreover, the interaction enables close relationship development between the residents and educators, which is vital for fluent knowledge sharing between individuals or among group of people (Wenger, 2002). The dialogue activities are combined by practice activities, such as guided direct practice with the educators/cadres/officers (Socialization) and personal practice day by day (Internalization). Eventually, the learning activities will improve

Table 8: Structural model evaluation

Hypothesis	Path model	Path coeficient (β)	P- value (T- value)			f^2 Effect size
			Total effect	Direct effect	Indirect effect	
H1	Dialogue → Practice	0.4305	0.0000 (9.7059) ***	0.0000 (9.7059) ***	-	0.2678
	Dialogue -> Practice -> Affective	0.1602	0.0000 (6.7927)	-	0.0000 (6.7927) ***	
	Dialogue -> Practice -> Affective -> Intention	0.0441	0.0000 (4.6246)	-	0.0000 (4.6246) ***	
	Dialogue -> Practice -> Affective -> WMB	0.0265	0.0006 (3.4543) ***	-	0.0006 (3.4543) ***	
	Dialogue -> Practice -> Affective -> Intention -> WMB	0.0219	0.0000 (4.4176) ***	-	0.0000 (4.4176) ***	
	Dialogue -> Practice -> WMB	0.0155	0.4610 (0.7378) ns	-	0.4610 (0.7378) ns	
H2	Dialogue → Affective	-0.0862	0.0700 (1.8158) ns	0.0351 (2.1131)**	-	0.0099
	Dialog -> Affective -> Intention	-0.0237	0.0529 (1.9400) ns	-	0.0529 (1.9400) ns	
	Dialog -> Affective -> WMB	-0.0143	0.0791 (1.7596) ns	-	0.0791 (1.7596) ns	
	Dialog -> Affective -> Intention -> WMB	-0.0118	0.0565 (1.9116) ns	-	0.0565 (1.9116) ns	0.1614
H3	Practice → Affective	0.3721	0.0000 (7.8042) ***	0.0000 (7.8042) ***	-	
	Practice -> Affective -> Intention	0.1024	0.0000 (4.7940) ***	-	0.0000 (4.7940) ***	
	Practice -> Affective -> WMB	0.0616	0.0005 (3.4941) ***	-	0.0005 (3.4941) ***	
	Practice -> Affective -> Intention -> WMB	0.0509	0.0000 (4.5173) ***	-	0.0000 (4.5173) ***	
H4	Facilities → Practice	0.3116	0.0000 (7.0327) ***	0.0000 (7.0327) ***	-	0.1403
	Facilities -> Practice -> Affective	0.1159	0.0000 (5.8869) ***	-	0.0000 (5.8869) ***	
	Facilities -> Practice -> Affective -> Intention	0.0319	0.0001 (4.0574) ***	-	0.0001 (4.0574) ***	
	Facilities -> Practice -> Affective -> WMB	0.0192	0.0012 (3.2486) ***	-	0.0012 (3.2486) ***	
	Facilities -> Practice -> Affective -> Intention -> WMB	0.0159	0.0001 (3.8825) ***	-	0.0001 (3.8825) ***	
	Facilities -> Practice -> WMB	0.0112	0.4778 (0.7104) ns	-	0.4778 (0.0112) ns	
H5	Facilities → Affective	0.4419	0.0000 (15.2637) ***	0.0000 (10.8264) ***	-	0.2884
	Facilities -> Affective -> Intention	0.1216	0.0000 (5.0871) ***	-	0.0000 (5.0871) ***	
	Facilities -> Affective -> WMB	0.0731	0.0003 (3.6800) *	-	0.0003 (3.6800) ***	
	Facilities -> Affective -> Intention -> WMB	0.0605	0.0000 (4.7728) ***	-	0.0000 (4.7728) ***	
H6	Affective → Intention	0.2751	0.0000 (6.2673) ***	0.0000 (6.2673) ***	-	0.0819
	Affective → WM Behavior	0.1655	0.0000 (6.4989) ***	0.0001 (4.0536) ***	-	0.0324
	Affective -> Intention -> WMB	0.1369	0.0000 (5.6685) ***	-	0.0000 (5.6685) ***	
H7	Intention → WMB	0.4975	0.0000 (14.3657) ***	0.0000 (14.3657) ***	-	0.3655
H8	Dialogue → WMB	0.1406	0.0000 (4.3524) ***	0.0015 (3.2008) ***	-	0.0246
H9	Practice → WMB	0.0361	0.0023 (3.07) ***	0.4596 (0.7400)ns	-	0.0012

ns = not significant; * p <0,10; ** p <0,05; *** p <0,01; (based on two-tailed significance)

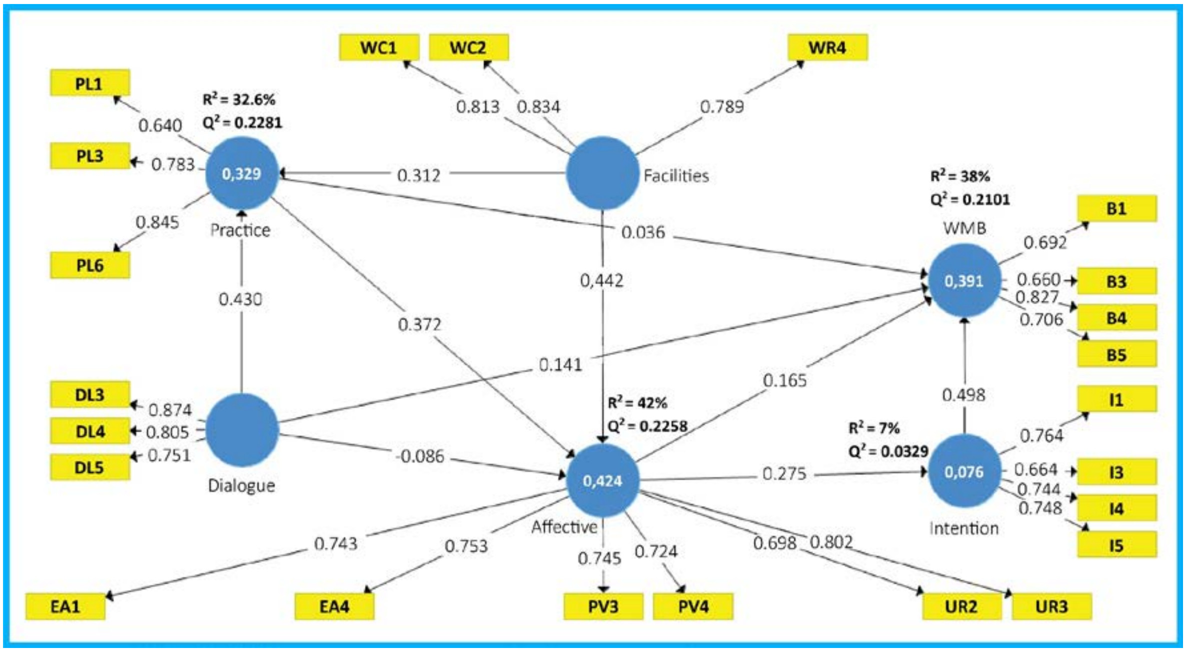

Fig. 7: Path coefficient significance of the proposed model

resident affective factors represented through personal and social responsibility, environmental and social perceived value, and environmental awareness (according to outer model test result). This finding also confirmed the qualitative finding from earlier study phase which revealed that most of the interviewed residents stated they could feel the benefits once they knew and practiced waste management directly (Ghazali *et al.*, 2021).

The effect of supporting facilities to practice-based learning and affective factors

The second extrinsic factor in the model was "Supporting Facilities", represented through routine waste collection systems, recycling facilities and the benefits of recycling products. A routine waste collection system refers to the availability of somebody-in-charge to collect separated waste routinely within the área. Meanwhile recycling facilities refer to the availability of tools to enable residents and or officers to recycle the separated waste directly in the area. It was hypothesized that "Supporting facilities" affect both "Practice-based learning" and "Affective Factors" directly. The path analysis result presented in Table 8, was proven that "Supporting facilities" directly affected both constructs significantly with P value for both 0.0000 (significant for all significance level). This finding supported the previous studies, which found a positive and significant relationship between facilities and affective factors (Wichai-utcha and Chavalparit, 2019; X. Liu *et al.*, 2019). However, the path analysis in Fig. 7 demonstrated that the effect of supporting facilities to affective factors is more significant than the effect of practice-based learning activities which typically nurture affective factors. This finding is in contrast to previous studies such as Kattoua *et al.* (2019), who contended that facilities' availability could not guarantee residents to participate in waste management activities unless they had enough environmental awareness and technical knowledge about it, which was resulted from learning activity (Ghazali *et al.*, 2021). There were two possible explanations for this phenomenon. First, it could be because the practice-based learning activities conducted in the ZWA program were not effective enough to nurture affective factors causing less impact on affective factors compared to supporting facilities. This argument is supported from the qualitative study in the previous phase (Ghazali *et al.*, 2021) which revealed that most of the educational contents in both learning approaches in the ZWA program focused heavily on technical knowledge, such as waste separation and waste recycling, while other crucial waste issues were neglected. Whilst educational content is vital in determining what affective factors are being nurtured (Sunarti *et al.*, 2021; Janmaimool and Denpaiboon, 2016; Song *et al*., 2016). Second, the supporting facilities variable could be more impactful to nurturing Affective Factors rather than learning activities because one of the indicators was about the expectance of residents toward recycling facilities' benefits. This indicator could represent their understanding of recycling activities, so they had expectation related to it. A previous study also showed that the expectation of benefits from recycling facilities was powerful in nurturing the residents' affective factors, especially perception of the activities' value (Wang *et al.*, 2020). Regardless of the different impacts given to Affective Factors, the path model test for both learning activities and Supporting facilities significantly shaped Affective Factors, indicating the vital role of the facilitator, either from the government or local leader, in initiating and facilitating the system.

The effect of affective factors resident affective factors on behavioral domains (Intention and waste management behavior /WMB)

According to the outer model analysis, the affective factors were well presented by three sub-variables: Personal and Social Responsibility, Perceived Value and Environmental Awareness. Personal responsibility points out the personal conscience or belief of responsibility about the waste issues due to their action, whereas social responsibility is someone's belief in society's role in waste issues (Table 6). The perceived value refers to the environmental and social value represented through perceived benefits once they have conducted the waste management activities. The benefits include a comfortable environment due to the cleanliness (environmental perceived value) or satisfaction feeling when they could help the waste collectors (socially perceived value). The last representation of Affective factors as the direct effect of social learning is environmental awareness, described by the feeling of whether their unfriendly behavior will cause harmful effects to their environment, such as environmental disaster (flood) or environmental pollution (Sunarti *et al.*, 2021; Zhang *et al.*, 2019). So, when the residents know the impacts of waste they dispose of (from dialogue-based learning), they know they have responsibility for waste management and are aware of the harmful impact if they do not manage their waste correctly. Table 8 indicated that "Affective Factors" were crucial to mediate Extrinsic factors (social learning and facilities) and behavioral factors (Intention and WMB). The path model analysis demonstrated that without "Affective Factors" being nurtured, learning activities and Facilities would not be able to improve behavior significantly, as all paths directly to Behavioral Domain (Intention and WMB) had an insignificant effect with accuracy model at moderate level (R^2 42%; Q^2 0.2258). Moreover, the path coefficient of learning activities (Dialogue-based and Practice-based) to WMB directly showed a low score (weak effect), indicating the vital function of Affective Factors to be nurtured as a mediator. This finding confirmed prior studies' findings which have proven that Learning Activities could not directly improve behavioral factors (Intention and WMB) unless Affective Factors mediated the relationship (Chen and Gao, 2020; Lissah *et al.*, 2021; X. Liu *et al.*, 2019; Pierini *et al.*, 2021; Sunarti *et al.*, 2021; Wang *et al.*, 2018). Based on the R^2 measurement effect, the model had moderate power to explain "Affective Factors", as much as 42%, implying that the model had 42% capability to predict the accuracy of Affective Factors. This capability was considered moderate, indicating that the Affective factors accurately predicted the path model. In terms of "Intention", Table 8 shows that Affective Factors had a significant effect on both "Intention" and WMB" directly. However, the P value of the indirect effects was higher than the P value to WMB. It means, the "Affective Factor" should improve "Intention" before affecting the WMB. However, according to the R^2 for Intention, the model had weak power to explain "Intention", which was only 7%. It indicated that the model had only 7% capability to predict the accuracy of Intention. This weak power could happen due to the absence of other Affective factors that played roles in this relationship. It confirmed what suggested by Sunarti *et al.* (2021), in which there were several layers of Affective Factors which were nurtured sequentially to influence "Intention". Thus, further research may explore more deeply about Affective factors and establish a causal relationship among the Affective Factors for a more authentic relationship to the Behavioral domain. Aside from the weak power of the model for "Intention, the mediating effect of Intention between the Affective Factor and WMB had a significant effect, similar to the finding from past studies (Loan *et al.*, 2017; Meng *et al.*, 2019; Wang *et al.*, 2020; Xu *et al.*, 2017).

CONCLUSION

Resident engagement in the MSWM system is vital to ensure its effectiveness because residentials are considered the most dominant waste generators in MSWM. It requires an integrated, long-term, and structured system to allow residents to learn about waste management for sustainable engagement in the waste management system. This study has revealed that social learning is implementable to improve resident engagement in the waste management system in cities from developing countries, like Bandung City. This study has revealed some insightful findings using a model analysis measuring the effect of social learning activities at the ZWA program in Bandung City, West Java, Indonesia. First, to be impactful, social learning activities in the program should implement both a dialogue-based and practice-based approach, in which dialogue-based learning precedes the practice. Dialogue-based learning activities are employed through discussion and training involving residents individually and collectively to allow interactive communication for knowledge transfer and build close relationships among residents and educators. Meanwhile, practice-based learning is employed through the direct practice of waste separation or recycling activities, either guided by the educators or doing it themselves. This activity aims to habituating them with new habits while also allowing residents to sense the waste management activity's benefits directly. Second, the study findings implied that supporting facilities are crucial to bolstering practice-based learning activities (through the waste collection system and recycling facilities) and nurturing affective factors (personal and social responsibility, perceived value and environmental awareness). Third, the direct effect of social learning activities is an improvement in residents' affective factor, which mediate behavioral factors (intention and behavior). The improvement in affective and behavioral factors becomes the crucial component of community engagement for sustainable participation in waste management. The study findings can guide the government in developing countries or environmental-based communities to start a community-based waste management system in a particular area, especially in the area that has supportive culture to enable social learning. It is recommended to pay more attention to the contents that highlight the harmful impacts of waste on the environment, individual and social roles in waste issues and also the benefits of doing waste management activities. The knowledge-sharing activities should also be accompanied by direct practice for habituation daily. It is also suggested to choose relevant problems as an example of waste issues to allow residents to be more connected to the problems. This study was only focused on investigating social learning effects on an individual level, so the further study may also focus on measuring the third loop learning effect (social capital) at the community level.

AUTHOR CONTRIBUTIONS

S. Sunarti conducted the literature review and design the research, collected and interpret the data, and prepared the manuscript writing. R.S.Y. Zebua collected data, processed and analyzed the data using SmartPLS, interpret the data and prepared the map using QGIS. J.H. Tjakraatmadja validated the questionnaire related to SECI Model, analyzed and interpreted the data, review the manuscript. A. Ghazali. validated the questionnaire related to SECI Model, interpreted the data, and review the manuscript. B. Rahardyan validated the questionnaire related to waste management behavioral variables, interpreted the data, and review the manuscript. Koeswinarno collected and interpret the data, and prepared the manuscript writing. Suradi collected and interpret the data, review the manuscript. Nurhayu collected and interpret the data, review the manuscript. R.H.A. Ansyah Interpreted the data, review the manuscript and managed the references.

ACKNOWLEDGEMENT

The authors wish to acknowledge valuable support to all mentors and supervisors of ZWA program in Bandung City, West Java, Indonesia who have given their efforts in facilitating this research. The authors thank LPDP who has supported on data collection process with the contract number [201708210811406]. Gratitude is also expressed to BRIN who has supported the data completion and the publication process. Thank you also for the two anonymous reviewers for their constructive comments and suggestions on an earlier version of this manuscript. Finally, the authors thank all participants who took a part in the interviews and surveys.

CONFLICT OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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ABBREVIATIONS

%	Percent
3R	Reduce, reuse, recycle
AVE	Average variance extracted
B1,B3,B4,B5	Measurement items for waste management behavior
BRIN	Badan Riset dan Inovasi Nasional
CAQDAS	Computer assisted qualitative data software
CoP	Community of practice
CR	Composite reliability
DL3,DL4,DL5	Measurement ítems for dialogue-based learning
DLHK	*Dinas lingkungan hidup dan kebersihan*
DTDE	Door to door education
e	Margin of error
EA1, EA4	Measurement ítems for environmental awareness
f2	Effect Size
GPS	*Gerakan pungut sampah*
HTMT	Heterotrait-monotrait ratio
I1,I3,I4,I5	Measurement item for Intention
K3	Kebersihan, ketertiban, keindahan
KANG PISMAN	Kurangi pisahkan manfaatkan
KBS	Kawasan bebas sampah
KM	Knowledge management
KSM	Kelompok swadaya masyarakat
MSWM	Municipal solid waste management
MSW	Municipal solid waste
NGO	Non-government organization
ns	Not significant
PKK	Pembinaan Kesejahteraan Keluarga
PL1,PL3,PL6	Measurement items for practice-based learning
PLS - SEM	Partial least square structural equation model
PV3, PV4	Measuremen items for perceived value
p	Standard seviation
p value	Probability value
q	1- p
Q2	Predictive significance
QGIS	Quantum geographic information system

R2	Model accuracy
RT	Rukun tetangga/hamlet
RW	Rukun warga/ community association
SECI	Socialization, externalization, combination, internalization
SIPSN	Sistem informasi pengelolaan sampah nasional
SPSS	Statistical package for the social sciences
t Value	Size of the difference
UR2,UR3	Measurement items for responsibility
WMB	Waste management behavior
WC1, WC2	Measurement items for waste collection
WR4	Measurement item for waste recycling
x	Sample size
Z	Confidence level
ZWA	Zero Waste Area

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HOW TO CITE THIS ARTICLE

Sunarti, S.; Zebua, R.S.Y.; Tjakraatmadja, J.H.; Ghazali, A.; Rahardyan, B.; Koeswinarno, K.; Suradi, S.; Nurhayu, N.; Ansyah, R.H.A. (2023). Social Learning Activities to Improve Community Engagement in Waste Management Program. Global J. Environ. Sci. Manage., 9(3): 403-426.

DOI: 10.22035/gjesm.2023.03.04

URL: https://www.gjesm.net/article_701156.html